Nonprofit Market Structure and Its Consequences

by

Danielle L. Vance-McMullen

Public Policy Studies
Duke University

Date:_______________________

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Rachel Kranton

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Seth Sanders

Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in Public Policy Studies
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ABSTRACT

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Abstract

This dissertation is comprised of three papers related to nonprofit market structure and its consequences. I begin with an essay that examines how the recent boom of nonprofit organizations affects giving using the context of the Combined Federal Campaign (CFC). I find that the nonprofit boom has not increased donations to nonprofit organizations. Since a fixed amount of charitable resources is split among more organizations, the average nonprofit receives less funding as the number of organizations grows. The second paper proposes a new definition of nonprofit markets based on individual-level donor behavior and donor-nonprofit network ties. Notably, the new market definition predicts donor substitution among organizations 58% more accurately than the standard nonprofit market definition based on an organization's subsector and geographic location. The CFC data and this donor-based market definition are also used to examine an important nonprofit policy issue—the relationship between market concentration and nonprofit spending on overhead. In the final essay, I study one of the processes by which competition in the CFC has increased over time—changes in the structure of government contracts. I examine whether fewer, but larger, contracts change performance. I find that contract consolidation does not significantly improve performance. Furthermore, I find no evidence that economies of scale exist in workplace giving.

Dedication

To my father, LeRoy Vance, with joy.

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I am thankful for my original Public Policy cohort at Duke, Puneet Chehal, Amy

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1. Chapter 1: Will Proliferation Destroy the Nonprofit Sector? Evidence on the Effects of Nonprofit Competition from the Combined Federal Campaign

1.1 Overview

The number of nonprofits in the United States is growing dramatically. Between 2003 and 2013, the United States experienced a 19.5% increase in 501(c)3 public charities. If aggregate giving does not increase proportionately, this trend could force nonprofits to operate with smaller average donations. Using aggregate and employee-level data from the Combined Federal Campaign (CFC), the nation's largest workplace giving campaign, this paper asks if increasing the number of nonprofit organizations affects giving. I find that the addition of new nonprofits did not substantially increase the charitable resource pool. It did not increase the proportion of individuals who gave. Furthermore, although donors gave slightly larger gifts after new organizations entered, the amount was not large enough to prevent the average nonprofit from losing revenue. Unless it is accompanied by substantial efficiency gains, proliferation will increase total sector spending on overhead and other fixed costs, leaving less for mission-related activities.

1.2 Introduction

The nonprofit sector is growing dramatically. Between 2003 and 2013, there was a 19.5% increase in registered 501(c)3 public charities (McKeever 2015). This level of growth is unprecedented. The IRS currently approves more than 50,000 new nonprofits annually, up from 20,000 per year in the 1960's to 1980's (Harrison & Laincz 2008). This growth is also dramatic when compared to for-profit firms. Between 2000 and 2010, there was an increase in nonprofit employment of 17 percent, which is more than the employment growth rate of government (8 percent) and business (-6 percent) over the same time period (Roeger et al. 2012). According to data from the Bureau of Labor Statistics, the number of nonprofit establishments meeting minimum size requirements for unemployment insurance reporting increased 15 percent between 2007 and 2012, while the number of for-profit establishments meeting this threshold decreased by 1 percent (2015).

Some nonprofit leaders warn that this growth may spawn an era of heightened, possibly destructive competition in the nonprofit sector. A January 2006 article in The Chronicle of Philanthropy, the leading publication covering the nonprofit sector, stated what many donors, politicians, and business leaders had hinted at for years: "As more and more organizations are created, leading to fierce competition for private donations and government aid, a growing number of people in and out of the nonprofit world are asking whether too many groups are overlapping one another and draining resources from those charities that do the best work," (Gose 2005). Other nonprofit leaders characterize competition as a distraction from mission and new nonprofits entering the territory occupied by established firms (often described as "duplication of services") as harmful to the success of the established nonprofits. From a public policy perspective, this issue becomes important when one considers that government expends grant dollars supporting nonprofit projects, contracts with nonprofits to secure public services, and supports nonprofits with tax exemptions and deductions at all levels of government.

Microeconomic theory based on principles of differentiated products predicts that the addition of new nonprofits will increase giving. The underlying assumption of this model is that donors have heterogeneous preferences for nonprofit characteristics and new nonprofits are not perfect substitutes for existing nonprofits. If this is the case, then at least some donors will find the new nonprofits to be a better match for their interests. Since they will benefit from greater nonprofit variety, they will increase their contributions when the number of nonprofits in a market increases. However, other theories suggest that the increase in contributions may be weak or nonexistent in the nonprofit sector. The theory of "warm glow" charitable giving suggests that individuals may care more about the act of donating than they do about the direct effect of their contributions on a cause (Andreoni 1989); in this case, the availability of better charitable matches would be less important to the donor. The degree to which additional variety is valued by donors has important consequences. If total donations to nonprofits do not increase in proportion to the number of organizations, then the average nonprofit will receive less donated revenue and giving to older organizations may be diverted to new rivals.

Empirical research on the effects of increasing nonprofit options finds support for both conclusions. In a field experiment, Eckel et al. (2017) find that providing two giving options to alumni of a university (a general fund option and a second, more specific giving option) increased giving by 37%, even though very few donors chose the second, more specific option. Van Diepen et al. (2009) examine donors who receive mailings from three competing charities. They find that when mailings from one charity increase in frequency, individuals not only give more to that organization, but they also give more to the competing charities. In a third laboratory experiment, Soyer and Hogarth (2011) find that individuals give more when presented with more comprehensive lists of nonprofit organizations, but that there are diminishing marginal returns. Interestingly, they also find that increasing the options actually generated more giving to the most popular of the organizations—donor "stealing" only occurred for the less well-known organizations.

These laboratory and controlled field experiments indicate that, under the right conditions, either donor growth or donor stealing can occur. But which conditions prevail in the larger nonprofit market? Unfortunately, understanding the relationship between nonprofit proliferation and donations in a non-experimental setting is difficult with the most common nonprofit data source, the IRS form 990. The sole paper investigating this topic uses this source and finds that increasing competition within an MSA increases the total public support (from individuals, foundations, and other sources) for all organizations in the area but decreases average gifts to each organization (Bose 2015). However, data limitations force that work to make two assumptions that my paper will overcome. First, I will be able to identify markets more accurately. The Form 990 only provides information on nonprofit headquarters; therefore, the common assumption is that a nonprofit only operates in and receives donations from the MSA of its headquarters. In contrast, I observe nonprofits in each location where they are raising funds, and so can handle nonprofits that are regional or national in operations and fundraising. Moreover, I will be able to observe individual-level giving decisions, while the Form 990 offers only information on aggregate giving to a nonprofit.

This paper will contribute to the debate on the effects of nonprofit proliferation by focusing on the relationship between proliferation and giving by individuals. To address this question, I use data on nonprofit participation in the Combined Federal Campaign (CFC). The CFC is the workplace giving program for federal employees and is the nation's largest workplace giving campaign. In 2013, more than 4 million federal employees were solicited through the campaign, and more than 650,000 gave. The 2013 campaign raised more than $250 million in donations. Reflecting trends in the sector as a whole, the number of nonprofits participating in the CFC has grown over the last decade, and more than 20,000 nonprofit organizations currently participate.

The CFC data span 2004-2014 and track aggregate federal employee giving for more than 160 geographic zones. Employees in each geographic zone receive a specific list of local, national, and international nonprofit options when making CFC gifts, and employees can only give to organizations on this list. Therefore, I consider each geographic zone to be a separate market for charitable giving. The regions differ in the number of nonprofits and in their growth patterns, making it possible to distinguish between changes due to the addition of new nonprofits and changes due to time, economic conditions, and federal workforce composition. Most importantly, I have individual-level CFC data for more than 55 geographic regions from 2008-2013.

I use a panel model with fixed effects to identify changes in giving caused by increases in the number of nonprofit giving options, after controlling for other factors. Nonprofits can choose to enter the CFC at the local or national level. National entry is plausibly unrelated to unobserved confounding variables, because a nonprofit's decision to enter nationally is unlikely to be driven by unobserved change in the performance of a local administrative zone. Furthermore, in my aggregate data, year and market fixed effects control for any unobserved factors that may affect the federal workforce as a whole or make one market consistently different from another. In my individual data, I use year and individual fixed effects, which control for unobserved factors affecting all federal employees in a particular year, as before, and all time-invariant individual characteristics, including an individual's perspectives towards altruism and giving in the workplace, to the degree that these perspectives don't change over time. This model means that my results are not driven by the changing composition of the federal workforce over time. I also control for changes in the local workforce over time, including demographic characteristics and income, and for time-varying local economic conditions, including natural disasters.

I find that that the addition of new nonprofits does not significantly increase the number of donors or substantially increase total giving. Under some functional forms, average gift size (giving per donor) increases in a statistically significant way, but the effect is not economically significant. Instead, these results show that, as the number of organizations grows, the dollars donated per organization decrease. This result holds in the individual data as well, where individual fixed effects are added to mitigate identification concerns regarding the changing nature of the federal workforce. Although I argue that measurement error and downward bias in organizational counts are unlikely, in the robustness section, I discuss possible sources of downward bias, including measurement error and omitted variables, and show that results are robust to including only campaigns judged to have low possibility of measurement error.

In cases where a donor switches giving to one of the new organizations, what patterns can be observed? In 42% of cases, donors switch from an organization within the same subsector; in 58% of cases, donors switch between subsectors to give to a new organization. The observed pattern of cross-subsector switching is somewhat surprising, as most analyses of the nonprofit sector assume that nonprofits are mostly competing with other organizations within their specific mission area. Organizations may be even more concerned about rising competition if they recognize that many of the donors they lose to new organizations are not going to organizations pursuing a closely related mission, widening the scope of organizations who are considered "competitors."

If the findings here hold more broadly, the boom in nonprofits in recent decades may be negatively affecting the efficiency of the sector and the public goods and social services it provides. As the sector continues to grow, we can expect the average organization to receive fewer charitable contributions. If each new organization incurs fixed administrative costs, then policymakers should be concerned that the nonprofit boom means fewer resources are available for public goods and service delivery. Unless new nonprofits are substantially more efficient, this is a problem. Government and foundations may want to respond by adjusting grantmaking guidelines to discourage duplication of services or encourage mergers, when appropriate. Policymakers may also become more cautious regarding social entrepreneurship initiatives, especially in fields with effective incumbent organizations.

This paper proceeds as follows: Sections II and III provide the institutional and theoretical context for the analysis; Section IV is a data overview; Section V and VI explain the method of analysis and how I have handled the identification challenges in this context; findings and robustness check results are in sections VII and VIII; Section IX provides some additional suggestive finding that serve to support my interpretation of the findings; and Section X concludes.

1.3 Institutional Context

The Combined Federal Campaign (CFC) is the employee giving program for the federal workforce. The federal workforce includes members of the military, postal workers, and all civilian employees of the federal government, making the CFC the largest workplace giving campaign in the nation. The CFC is part of a broader group of workplace giving programs like the United Way. Together, workplace giving programs reach about 25% of American workers (NCRP 2003), with about $4 billion collected annually (Giving USA 2007). Both the funds raised by the CFC and the number of participating charities have risen since the program was formalized in 1971 by President Nixon.

For the purposes of the CFC, the country is divided up into approximately 150 geographic zones. Each geographic zone is made up of one or more counties. In some areas of the country, CFC geographic zones encompass a whole state or even a multi-state area. The 2013 map of CFC geographic zones is shown in Figure 1.

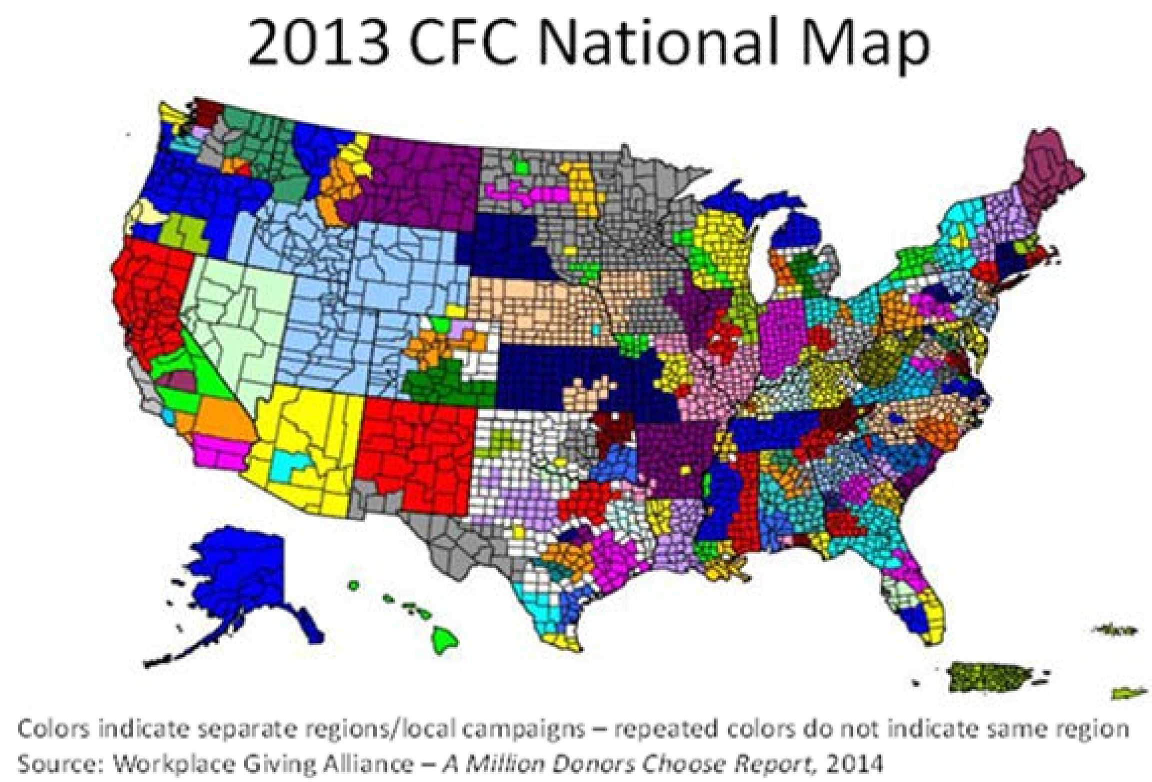
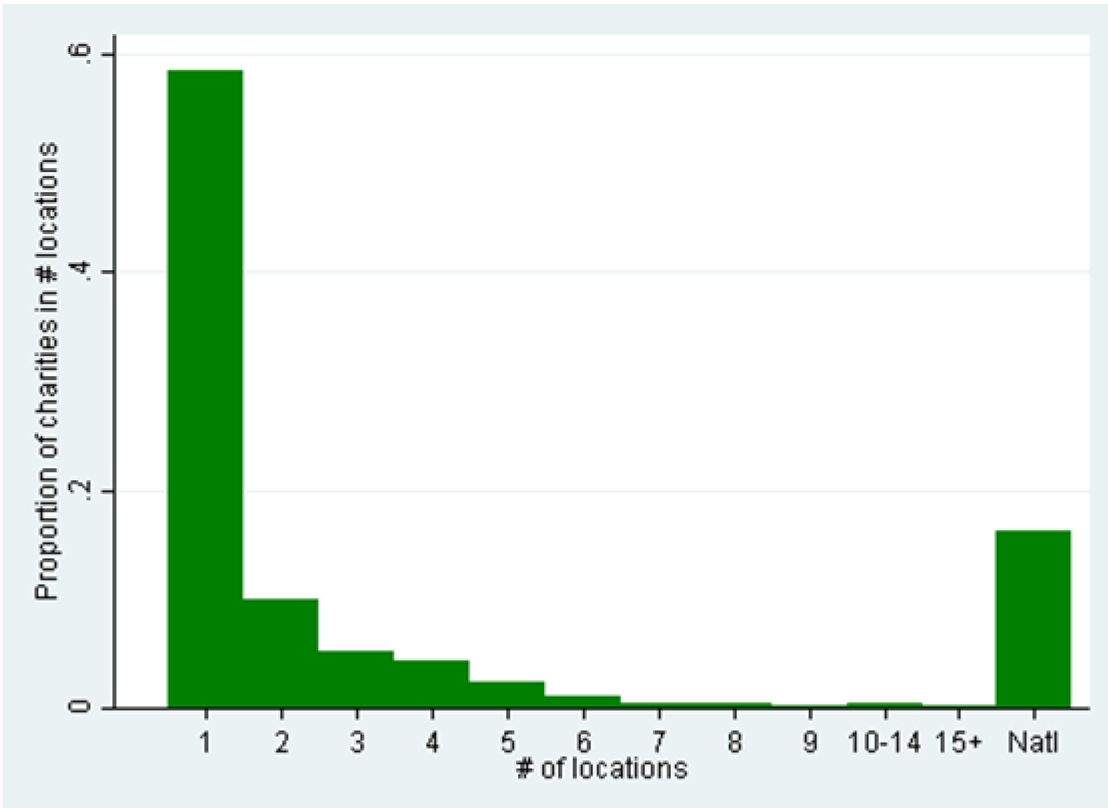


Figure 1: CFC Geographic Zones

Using the CFC to study the relationship between nonprofit proliferation and donor revenues has three analytical advantages. First, the charities that donors can contribute to are tightly regulated. This minimizes some common concerns related to market definition. Researchers attempting to define nonprofit markets typically face issues with determining the appropriate market borders and observing the charities present in the market. In other contexts, individuals give to nonprofits in cities far from their homes (such as alma maters, etc.). Furthermore, nonprofit locations can be difficult to determine because researchers may only observe headquarter locations rather than local and regional offices.

In contrast, the CFC is structured by federal law and national rules. Thus, a researcher can perfectly observe each of the closed markets (shown in Figure 1) and the charities that a donor can contribute to. Under federal rules, an organization's eligibility is tied to its operating locations. Charities can participate either at the national level or at the local level. To participate at the local level a nonprofit must demonstrate that it has a "substantial" program presence in or adjacent to the campaign's geographic borders (OPM 2013). To participate at the national level, a nonprofit must demonstrate that it has provided services in 15 or more states or a foreign country in the prior three years. Participating at the national level means that charities will be listed in the charity booklet for every geographic zone across the country. Currently, more than 2000 charities participate at the national level. Figure 2 shows how many geographic zones each charity participates in.

Second, regulations concerning CFC operations also minimize concerns about endogenous solicitation efforts. In most models, giving by individuals is determined both by the charities in the market and the solicitation efforts of those charities. If charities change their solicitation when competition increases, it can be difficult to separate the effect of competition from the effect of solicitation.



Note: Years 2008 through 2013 are included. Organizations without an EIN (approx. 500 org-years) are excluded from the graph. Most of these organizations are present in 1 or 2 locations.

Figure 2: Number of Local Campaign Zones for Each Organization (EIN)

In the case of the CFC, charities can do very little to influence donor choices. This is because the information provided to donors is tightly controlled. Annually, each federal employee receives a list of eligible charities specific to their geographic zone. The format of this list is tightly controlled. Information on the eligible charities is limited to the charity’s name, categories of work, overhead ratio, website, and a 25-word statement. For an example, see Figure 3. Employees who choose to donate can do so by means of a paper pledge card (shown in Figure 4) or by using one or more online giving systems. Charities are also limited in the mailings and communications they are allowed to have with potential federal donors.

In addition, the Combined Federal Campaign is both important in its own right and understudied. Even though the CFC is the largest workplace giving campaign in the nation, few empirical analyses exist that attempt to understand the influences on giving to the CFC. Most noticeable of these is Bowman (2006), which analyzes the role of charity overhead ratios on donor decisionmaking within the CFC. Empirical studies on workplace giving outside of the CFC are also limited, but have been increasing in recent years (see Osili et al. 2011, Agypt et al. 2012, Leslie et al. 2012, Nesbit et al. 2012).

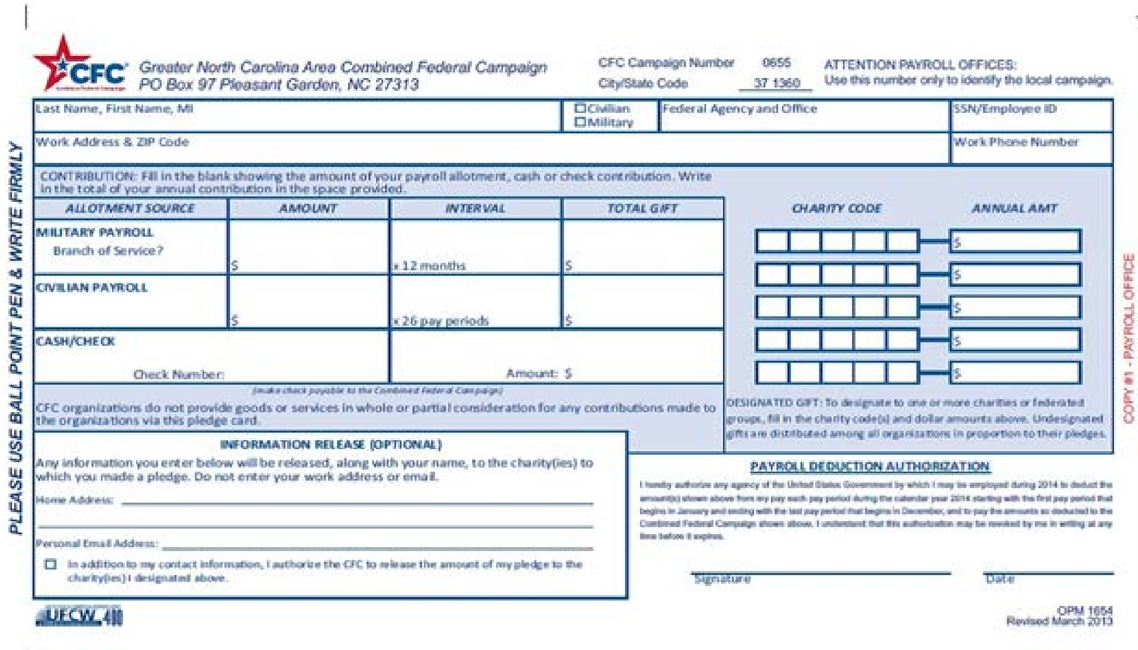
Sample Charity Listing

11405 ABC Charity (Alpha-Charity) (800) 555-5555 www.abccharity.org EIN#123456789 ABC Charity attacks the causes of hunger and poverty by promoting effective and innovative community-based solutions that create self-reliance, economic justice, and food security. 15.8% P,S,K

(a) Generic listing information

(b) Sample list of charity options

Figure 3: Sample of Charity Information Observed by Employees



CFC Greater North Carolina Area Combined Federal Campaign
PO Box 97 Pleasant Garden, NC 27313

CFC Campaign Number 0655
City/State Code 37 1360

ATTENTION PAYROLL OFFICES:
Use this number only to identify the local campaign.

PLEASE USE BALL POINT PEN & WRITE FIRMLY

Last Name, First Name, MI	☐ Civilian ☐ Military	Federal Agency and Office	SSN/Employee ID
Work Address & ZIP Code			Work Phone Number

CONTRIBUTION: Fill in the blank showing the amount of your payroll allotment, cash or check contribution. Write in the total of your annual contribution in the space provided.

ALLOTMENT SOURCE	AMOUNT	INTERVAL	TOTAL GIFT
MILITARY PAYROLL Branch of Service?	$	x 12 months	$
CIVILIAN PAYROLL	$	x 26 pay periods	$
CASH/CHECK Check Number:		Amount: $	

(make check payable to the Combined Federal Campaign)

CFC organizations do not provide goods or services in whole or partial consideration for any contributions made to the organizations via this pledge card.

CHARITY CODE	ANNUAL AMT
	$
	$
	$
	$
	$

DESIGNATED GIFT: To designate to one or more charities or federated groups, fill in the charity code(s) and dollar amounts above. Undesignated gifts are distributed among all organizations in proportion to their pledges.

INFORMATION RELEASE (OPTIONAL)

Any information you enter below will be released, along with your name, to the charity(ies) to which you made a pledge. Do not enter your work address or email.

Home Address: ______

Personal Email Address: ______

☐ In addition to my contact information, I authorize the CFC to release the amount of my pledge to the charity(ies) I designated above.

PAYROLL DEDUCTION AUTHORIZATION

I hereby authorize any agency of the United States Government by which I may be employed during 2014 to deduct the amount(s) shown above from my pay each pay period during the calendar year 2014 starting with the first pay period that begins in January and ending with the last pay period that begins in December, and to pay the amounts so deducted to the Combined Federal Campaign shown above. I understand that this authorization may be revoked by me in writing at any time before it expires.

Signature Date

COPY #1 - PAYROLL OFFICE

OPM 1654
Revised March 2013

Figure 4: Sample of Paper Pledge Card

1.4 Theoretical Framework

There is no common, agreed-upon theory for donor giving behavior as the number of nonprofit choices in a market increases. Furthermore, important theories exist that predict that giving will increase, decrease, and remain the same. The empirical evidence in this paper provides support for some theories over others, but does not attempt to prove that one theory applies to the exclusion of others.

Microeconomic theory based on principles of differentiated products predicts that the addition of new nonprofits will increase giving. Many (if not all) nonprofits work to differentiate their goods and services from those of other nonprofits (Aldashev and Verdier 2010). Donors also have heterogeneous preferences, demonstrated by their attraction to different types of charitable causes and different ideas about how missions are best achieved. Given these preferences, when more nonprofits enter a market, the quality of the donor-nonprofit match improves. When match improves, donors derive more utility from donating to charity. As the attractiveness of charitable giving increases, donors contribute more and reduce personal consumption. Donors who were previously giving to nonprofits to which they were not well-matched increase their gifts and former non-donors who were unhappy with the previous nonprofit options become donors. Thus, aggregate giving increases.

There are several theoretical reasons why new organizations might not increase aggregate giving. One reason is because donors may gain utility directly and solely from the act of giving, which the literature terms "warm-glow" motivation for giving (Andreoni 1989). It is only the act of giving, not the goods and services produced by the nonprofit, that changes donor utility. Donors might experience a warm glow because of religious beliefs, social recognition, or feelings of self-esteem driven solely by the amount given. In this case, although a new nonprofit may be a better match for the donor's preferences, the warm glow value of donating a dollar does not increase. Therefore, donors do not increase donations as the number of nonprofits in the market increases.

Another possibility is that donors have fixed philanthropic budgets that are not swayed by the number or makeup of nonprofits in their market. This framework does not deny that nonprofits and consumer preferences are heterogeneous or that new nonprofits allow donors to improve their match. However, because of their fixed budgets, donors in this framework are not expected to increase their giving, although donors may shift their gifts to more preferred organizations. This idea of budgeting for specific types of expenses is taken from the psychology and behavioral economics concept of “mental accounting” (Thaler 1999). In this framework, spending is not equally fungible across all categories of consumption. Instead, consumers can partition their spending by mentally earmarking funds for certain activities, including charitable giving. Indeed, the Christian concept of tithing—where 10% of one’s income is reserved for charitable endeavors—could be seen as a form of charitable earmarking. Furthermore, past qualitative research has established that individuals mentally set charitable giving budgets, but often regard these budgets as malleable (LaBarge and Stinton 2014). The mental accounting explanation differs from the warm glow explanation in an important way. Under mental accounting, the arrival of new nonprofits may increase donor utility without increasing giving; under pure “warm glow” utility is determined solely by the amount donated and does not increase if giving does not increase.

It is also possible that giving remains the same because donors see the new nonprofits as no different from the old ones. They find them to be perfect substitutes for the old nonprofits. In this case, donor utility remains the same, and donors are indifferent between giving to the old and the new nonprofits. Since they are indifferent, they arbitrarily select either a new or old nonprofit for their gift. When a new nonprofit is selected, funds are diverted from whatever nonprofit received the donation in the previous year. In this case, like in the warm glow case, donor utility does not increase as the number of nonprofits increases.

Finally, there are theoretical reasons to believe that increasing the number of choices may decrease giving. The “choice overload” hypothesis states that too much choice can be stressful for decisionmakers and may even prevent people from making any choice at all (Iyengar and Lepper 2000). This phenomenon has been documented in a number of choice contexts, although other work shows no relationship.[1] If this applies in the context of charitable giving, then it is possible that increasing the number of choices may not only decrease giving but also overall donor utility.

1.5 Data

To understand the relationship between nonprofit proliferation and giving, I use data on nonprofit participation in and employee giving through the CFC. The CFC data span 2004 to 2013 and track all federal employee giving for more than 160 markets/geographic regions. In addition, I have individual-level CFC data for more than 55 markets from 2008 to 2013.

1.5.1 Aggregate data

The CFC has provided aggregate data from 2004 to 2013 for this work, as well as data on participation by nonprofit organizations from 2008 to 2013. The data cover

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[1] For contradictory overviews see Scheibehenne, Greifeneder, and Todd (2010) as well as Chernev, Böckenholt, and Goodman (2010).

charities and giving for each of approximately 163 campaign regions. The CFC charity data set includes the list of participating charities (local and national), the federation (if any) that the charity is affiliated with, the charity's stated areas of work, its approximate overhead rate, and the EIN number of the charity. The EIN number allows for matching with charitable tax returns, which provide data on charitable finances.

The CFC aggregate giving data set includes the total giving, the giving to each national federation (and charities participating outside of federations at the national level), the total giving to local charities, the total number of employees, and the number of employees who made donations. Table 1 shows summary statistics for the aggregate data provided by the Office of the CFC. Total pledges are inflation-adjusted to 2011 dollars.

The table shows that the number of donors and dollars pledged to the CFC have decreased substantially over time. The total number of employees solicited as part of the CFC increased between 2008 and 2010, and then decreased somewhat from the 2010 high. Therefore, donors per employee, which I will refer to as participation and which is expressed as a proportion, has decreased. In fact, participation decreased from approximately 28 percent to 16 percent over this time period. Furthermore, giving per employee has decreased over time while giving per donor has increased. It appears this is because the smallest donors have been the ones to drop out of the CFC. These trends are quantified in Table 2 and illustrated in Figure 5.

Table 1 also shows that the number of local geographic zones has decreased. This is the result of consolidation of geographic zones over the time period in question. Meanwhile, the number of national charities has increased. Furthermore, all quartiles of the distribution of local charities have increased; in 2013, the typical federal employee has more options than she did in 2010 for both local and national organizations. Despite the growth in options, the number of unique local charities participating has declined somewhat.[2]

[2] It is possible for the number of local charities in each zone to increase while the number of unique local charities decreases because many organizations are operating in multiple local administrative zones, but do not meet the requirements to participate nationally.

Table 1. Aggregate Summary Statistics

	2008	2009	2010	2011	2012	2013
Total Pledges (2011 dollars)	270,579,828	278,774,030	274,925,782	257,178,159	238,429,053	190,819,836
Total Employees Solicited	3,634,673	3,692,079	3,765,134	3,749,031	3,748,362	3,747,245
Total Number of Pledges	1,016,897	995,609	928,428	871,731	772,988	589,658
Participation	0.280	0.270	0.247	0.233	0.206	0.157
Per Capita Pledge (2011 dollars)	74.44	75.51	73.02	68.60	63.61	50.92
Average Pledge (2011 dollars)	266.08	280.00	296.12	295.02	308.45	323.61
Number of Campaign Zones	241	224	207	195	182	161
Number of National Nonprofits	2220	2313	2389	2497	2545	2583
Mean Number of Local Nonprofits	148.9	111.8	198.0	208.1	220.1	235.7
25th Percentile Locals	61.0	44.0	88.0	91.0	96.0	97.0
Median Locals	105.0	78.5	145.0	150.0	159.0	174.0
75th Percentile Locals	208.5	140.0	258.0	266.0	276.0	285.0
Total Unique Local Entities	20,694	16,198	22,261	21,930	21,271	20,746

Note: Local nonprofit counts for 2008 and 2009 may be unreliable. Results are checked for robustness to excluding these two years. Per capita pledges, average pledge, and participation rate are each calculated at a national level. Per capita pledges are calculated by dividing the total pledges by the number of employees solicited nationwide; average pledge is calculated by dividing the total pledges by the number of pledges nationwide; and participation is calculated by dividing the number of pledges nationwide by the total employees solicited nationwide.

Table 2. Distribution of Dependent Variables

	2008	2009	2010	2011	2012	2013
Per Capita Pledge (2011 dollars)	74.44	75.51	73.02	68.60	63.61	50.92
Mean Per Capita Pledge	63.31	63.38	64.31	61.44	58.06	49.09
SE Per Capita Pledge	34.53	34.59	37.70	40.82	37.63	34.22
25th pctile Per Cap Pledge	40.37	40.18	40.05	35.31	33.70	28.65
Median Per Cap Pledge	55.27	56.69	55.93	51.98	50.56	40.18
75th pctile Per Cap Pledge	81.03	78.10	73.90	71.64	66.12	56.23
Average Pledge (2011 dollars)	266.08	280.00	296.12	295.02	308.45	323.61
Mean Avg Pledge	249.78	261.04	273.68	276.37	286.03	299.00
SE Avg Pledge	81.09	86.99	91.01	100.84	99.25	106.39
25th pctile Avg Pledge	197.49	206.70	217.05	207.30	213.90	227.80
Median Avg Pledge	247.74	256.52	267.69	275.43	284.41	291.67
75th pctile Avg Pledge	295.23	312.01	330.48	331.31	339.91	355.11
Participation	0.280	0.270	0.247	0.233	0.206	0.157
Mean Participation	0.257	0.244	0.239	0.224	0.202	0.167
SE Participation	0.110	0.100	0.109	0.097	0.091	0.103
25th pctile Participation	0.176	0.169	0.166	0.160	0.143	0.110
Median Participation	0.248	0.235	0.220	0.211	0.191	0.141
75th pctile Participation	0.318	0.296	0.289	0.269	0.236	0.200

Note: Per capita pledges, average pledge, and participation rate are each calculated at a national level. Per capita pledges are calculated by dividing the total pledges by the number of employees solicited nationwide; average pledge is calculated by dividing the total pledges by the number of pledges nationwide; and participation is calculated by dividing the number of pledges nationwide by the total employees solicited nationwide. The 25th percentile, median, and 75th percentile statistics are from the campaign-level distributions of these variables. Each of the three statistics is calculated at the campaign level, and the distribution is evaluated and reported.

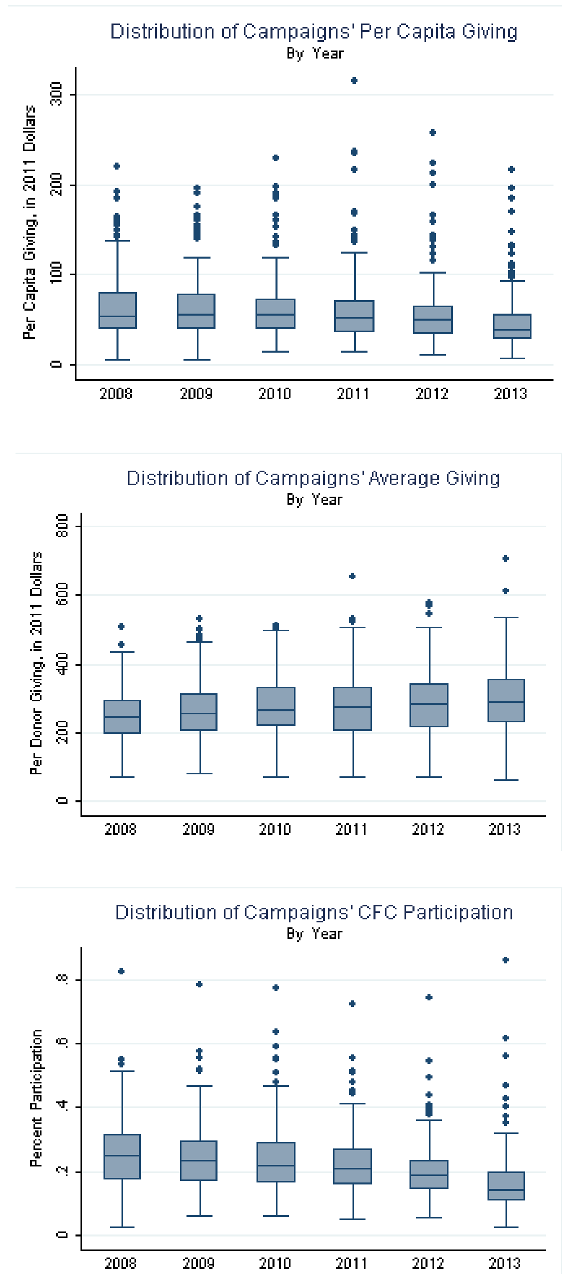


Figure 5. Variation in Dependent Variables

1.5.2 Individual giving data

The CFC has also provided anonymized, individual-level giving data for 62 local geographic zones from 2008 to 2013. The data comes from CFC Nexus, a software vendor for the CFC. These individual-level data include observations for 162,000 individuals matched to donor IDs. Individuals are matched to donor IDs when they give using the CFC Nexus online form rather than the paper form. Individuals giving using a paper form are excluded from these analyses because they cannot be traced over time. The 162,000 individuals in the analysis data make about approximately 227,000 pledges over time, with about 39,000 individuals appearing in two years or more. Individuals matched to donor IDs are

For each donor, the individual data reveal both the total the donor pledged for the year and the charities the donor selected. The data include information both on the total amount an individual donates in a year, which I refer to as the individual's pledge, and the amount the individual donates to each charity he or she selects, which I refer to as an individual's gifts. An individual donor makes one pledge each year, but the donor often makes multiple gifts by splitting the pledge among multiple nonprofit organizations. Summary statistics for this data are included in Table 3.

The increase in pledges shown in Table 3 reflects the increasing coverage of the individual data (increased use of the online giving system) over the period between 2008 and 2013. As shown, the number of local geographic zones covered increased to 62 over this time period. The individual data summarized in Table 3 include some additional

Table 3. Individual Summary Statistics

	2008	2009	2010	2011	2012	2013
Total Pledges (2011 dollars)	3,151,304	6,898,952	12,152,758	18,055,893	27,219,634	36,261,569
Mean Pledge (2011 dollars)	416.12	434.61	401.35	429.93	434.03	527.13
25th Percentile Pledge	125.37	125.82	103.16	120.00	117.57	115.87
Median Pledge	271.64	272.61	268.21	260.00	254.73	251.05
75th Percentile Pledge	543.27	545.21	536.41	520.00	509.46	627.63
Number of Pledges	7,573	15,874	30,280	41,997	62,713	68,790
Number of Campaign Zones	17	25	37	47	59	62
Number of National Nonprofits	2,220	2,313	2,389	2,497	2,545	2,583
Mean Number of Local Nonprofits	226.9	203.0	312.9	313.0	310.1	367.2
25th Percentile Locals	132.5	110.0	160.0	171.0	174.0	185.0
Median Locals	235.0	164.0	246.0	266.0	286.0	293.0
75th Percentile Locals	292.0	263.0	408.0	373.0	348.0	399.0

Note: Sample includes only those individuals and pledges and campaigns in the estimation sample. The estimation sample is limited to those individuals who donate through the CFC Nexus software and therefore can be traced over time (i.e. no paper pledges).

changes in giving patterns over this time period, although these may the result of selection effects as the composition of the individual data changes. While the median pledge in this data decreased slightly over the time period, the mean and 75th percentile increased substantially. It appears that either donors in the individual giving sample were increasing their pledges or larger donors were switching from paper to online giving over this time period. Since gifts on the paper form do not appear in my sample, these donors would only be captured when they began making online gifts. Or, the local geographic zones that switch to the software system may have larger gifts than the average zone. The mean pledge was $394 and the median was $200 (when both online and paper pledges are considered). The distribution of pledges was substantially skewed. Pledging small amounts was most common, although a few large pledge outliers exist. Table 4 compares the full data with the online giving sample (the selected subsample) and the paper giving records (the excluded data).

When individuals make their pledges through the online system, CFC Nexus captures several fields that may be used to infer additional demographic characteristics. First, the office where the employee works is recorded, with the address and zip code information typically included, which will make it possible to tie the individual to time-varying characteristics specific to that worker's location. The individual's gender can be inferred for about 60% of the records through gendered titles (Mr./Mrs./Ms./Miss). For 82% of the records, the data reveal if the employee is civilian or military.

There are 22,500 nonprofits with gifts over the seven years in the individual

Table 4. Giving Distribution by Type of Pledge

	N	Mean	Std Dev	Min	25th Pctile	Median	75th Pctile	Max
All Individual Data								
2008 Pledges	23418	181.711	(245.1900)	1.04	54.33	125.37	226.71	10052.64
2009 Pledges	96244	181.343	(332.3806)	0.01	52.42	109.04	226.47	42039.04
2010 Pledges	176133	169.277	(236.1515)	0.01	51.58	107.28	209.41	18774.49
2011 Pledges	220601	178.831	(292.2128)	0.01	52.00	120.00	240.00	23690.00
2012 Pledges	291020	176.585	(251.0258)	0.01	50.95	117.57	235.13	26717.10
2013 Pledges	476752	205.995	(457.5694)	0.01	50.21	125.53	251.05	171389.02
Individual Data Subsample								
2008 Pledges	16655	189.211	(240.3018)	1.04	54.33	125.37	250.74	6111.82
2009 Pledges	35704	193.250	(248.1145)	1.05	62.91	125.82	262.12	9436.37
2010 Pledges	64578	188.187	(250.1931)	1.03	53.64	123.79	247.58	10521.97
2011 Pledges	94266	191.542	(255.9155)	1.00	60.00	120.00	250.00	18200.00
2012 Pledges	142612	190.865	(257.2967)	0.98	51.93	117.57	246.89	17831.00
2013 Pledges	179913	201.551	(287.8567)	0.97	50.21	120.70	251.05	14483.72
Individual Data Excluded								
2008 Pledges	6763	163.241	(255.9144)	1.04	54.33	108.65	208.95	10052.64
2009 Pledges	60540	174.321	(373.0873)	0.01	41.94	104.85	209.70	42039.04
2010 Pledges	111555	158.330	(226.9095)	0.01	37.14	103.16	206.23	18774.49
2011 Pledges	126335	169.347	(316.2653)	0.01	46.80	104.00	208.00	23690.00
2012 Pledges	148408	162.863	(244.0635)	0.01	47.03	101.89	229.26	26717.10
2013 Pledges	296839	208.688	(534.8152)	0.01	50.21	125.53	251.05	171389.02

Note: "Individual Data Subsample" is comprised of only those donors who give through the online system and are therefore traceable longitudinally, making them the preferred subsample for analyses. "Individual Data Excluded" is comprised of donors not contributing through the online system (generally paper pledges).

giving database. In 2014, nearly 16,000 nonprofits are represented, although only 7,400 of these are tied to user IDs rather than paper pledges. One of the research benefits of using the CFC data is the ability to observe gifts to multiple organizations by one individual. Still, the majority of the pledges in this data set (60%) are directed to only one nonprofit. An additional 25% of pledges are divided among two or three nonprofits. Approximately 11% of pledges are split between four or five nonprofits. The remaining 9% of gifts go to six or more nonprofits. On average, those donating through the Nexus online system (and participating in more than one year) split their pledge among more charities than those donating by paper pledges.

Although a large number of charities receive gifts through the CFC, most gifts are concentrated among a very small group of charities. Within the individual data, I find that 80% of gifts go to 13.0% of the charities in 2013. Table 5 expands on this statistic for 2014, showing that 10% of the charities receive 75% of the gifts, and 20% of the charities receive 86% of the gifts. The concentration of giving grew during the time period in the data, with 10% of charities receiving 62% of gifts and 20% receiving 76% of the gifts in 2008.

Table 5 Concentration of Gifts to Organizations, 2013

Pct. Charities	Pct. Revenue
5	63.50
10	75.66
15	82.36
20	86.78
25	89.89
30	92.21
35	93.99
40	95.39
45	96.48
50	97.34
55	98.02
60	98.54
65	98.96
70	99.28
75	99.53
80	99.71
85	99.85
90	99.93
95	99.98
100	100.00

Note: Sample includes all individual donors and all pledges except those to "Undesignated".

1.5.3 Data for control variables

Three main types of control variables are used in the analysis to control for time-varying characteristics of the local geographic zones. I control for characteristics of federal workers, economic conditions, and disasters. Table 6 shows summary statistics for the control variables available.

Data on employee characteristics comes from three sources. The Office of Personnel Management releases individual-level data on federal civilian employees matched to the state of employment. Included employee characteristics are gender, occupation category, work status, salary, length of service, age range, and agency. Gender, occupation category, and work status are categorical variables, and I convert this to the proportion of employees in a zone falling into each category (proportion female, for instance). I use Congressional Research Service data on the size of the postal workforce by state in 2009-2014. I use annual military demographics reports (and the military census in earlier years) to obtain annual military personal counts at the state level. The counts by state-year from these three data sources allow for the estimation of the proportion postal employees and proportion military employees by state-year. When calculated in this way, North Carolina has the largest percentage military and Maine has the lowest percentage military. Iowa has the highest percentage postal, and Hawaii has the lowest.

To generate economic controls for each geographic zone in each year, I used unemployment data from the Bureau of Labor Statistics and per capita personal income data available from the Bureau of Economic Analysis. To determine an unemployment rate for each local geographic zone and year, I divided the total civilian unemployment in the within-zone counties by the total civilian labor force in the counties.

Disaster information comes from the Federal Emergency Management Agency (FEMA). Information on all presidentially-declared disasters from 2004-2014 was recorded from the FEMA website. Disaster data specifies the geography, disaster type, and financial allocations related to the disaster. Only disasters during the campaign period (Sept-December) are included are included in the count and dollar amount variables. The disaster counts include disasters of all types within the state, and the disaster dollar amount is the sum of individual and public allocations related to disaster recovery within the state, adjusted to 2011 dollars.

Two versions of an urbanness measure are constructed. The first generates county-level population density measures using populations from the U.S. Census Bureau (2000-2010) and American Community Survey (2011-2014) and the U.S. Census Bureau's 2010 estimate of land area. Then these county-level measures are converted to a measure for the local geographic zone using the weighted average based on the population of each county. Urbanness is also measured by the Rural-Urban Continuum Codes (USDA). This codifies the population of urban counties and the population and proximity to urban areas of non-urban counties. Because these codes are ordinal, there is no clear way to generate measures for the local geographic zones. I choose to measure the urbanness of a zone by the code of its most urban portion (this is the minimum value of the RUCC).

Finally, the local geographic zone's region was assigned based on the Census' 9-region and 4-region categories. When zones span multiple sates, the region was assigned based on the majority of the counties within the geographic zone.

Table 6. Summary Statistics for Control Variables

	Mean	Std Dev	Min	25th Pctile	Median	75th Pctile	Max
Civil Employee Demographics							
Proportion Female	0.437	(0.038)	0.286	0.411	0.440	0.466	0.523
Proportion Permanent Status	0.876	(0.035)	0.731	0.861	0.881	0.898	0.937
Proportion Professional Category	0.246	(0.037)	0.165	0.222	0.243	0.266	0.392
Proportion Administrative Category	0.319	(0.050)	0.199	0.283	0.325	0.343	0.487
Average Length of Service	13.13	(0.99)	10.24	12.44	12.97	13.73	15.87
Average Age	45.90	(0.63)	43.45	45.47	46.00	46.34	47.50
Average Salary	69,806	(6,423)	56,438	65,639	69,074	73,981	95,703
Employee Type							
Proportion Postal Service	0.199	(0.103)	0.030	0.123	0.165	0.280	0.503
Proportion Uniformed Military	0.285	(0.171)	0.008	0.151	0.310	0.415	0.655
Economic Conditions							
Unemployment Rate	0.079	(0.024)	0.025	0.062	0.078	0.093	0.170
Per Capita Personal Income	36,700	(6,997)	20,893	32,081	35,238	39,077	64,797
Disasters							
Number of Disasters (Jan-Dec)	4.0	(7.5)	0.0	1.0	2.0	4.0	57.0
Number of Disasters (Sept-Dec)	0.9	(1.7)	0.0	0.0	0.0	1.0	11.0
Disaster Allocation (Jan-Dec)	173.4	(669.2)	0.0	2.3	19.6	72.5	4,817.5
Disaster Allocation (Sept-Dec)	2,138.7	(15,062.0)	0.0	0.0	0.0	20.1	125,390.7
Urbanness							
Population Density (Weighted)	718.4	(2,615.6)	10.0	138.2	290.4	640.0	37,142.4
Observations	1210						

Note: Proportion postal and proportion military data not available for 2008. Disaster allocations measured in millions of 2011 dollars. Salary and Per Capita income measured in 2011 dollars.

1.6 Method of Analysis

My approach takes advantage of the fact that federal employees in each local geographic zone face a separate list of nonprofit options when making CFC gifts. These options have grown differentially across geographic zones, allowing me to distinguish between changes due to new nonprofits and changes due to time, economic conditions, and federal workforce composition.

The two data sources—the aggregate data and the individual-level data—are able to answer different questions. The aggregate data include not only information on giving, but also information on the number of donors and the number of employees solicited. Therefore, this data source can answer questions about giving per employee, average giving (giving per donor), and participation (donors per employee, expressed as a proportion). The individual data only include records for those who donate. Therefore, the data can only answer questions regarding average giving. However, since the data also includes information on specific pledges, they can answer more questions about patterns of giving and substitution among charities.

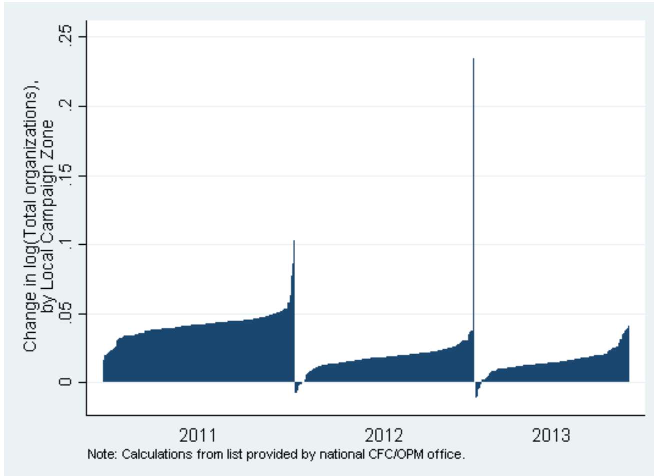
Using the aggregate data, I use OLS regression to understand the relationship between the number of charities in a geographic zone, which is the relevant market in the CFC, and giving. The main giving statistic I am interested in is giving per employee (each solicited employee is a potential donor). I later separately evaluate two components that influence this statistic, participation and giving per donor.

The log-log functional form is a straightforward regression of log giving per employee (total giving divided by number of employees) on the log number of nonprofits in a zone (there are 200+ CFC geographic zones/markets during this time period, and the number of nonprofits includes both local and national nonprofits on the CFC list), vectors of demographic and economic controls, and fixed effects for the zone and year. Subscript *zy* indicates that each of these variables is measured at the zone-year level in the aggregate data. Standard errors are clustered at the zone level. The log-log form assumes that percentage changes in the number of nonprofits in a market are more important than absolute number changes, which is the unit of analysis in a linear model. This form also reduces concerns about heteroskedasticity and skewness in the errors.

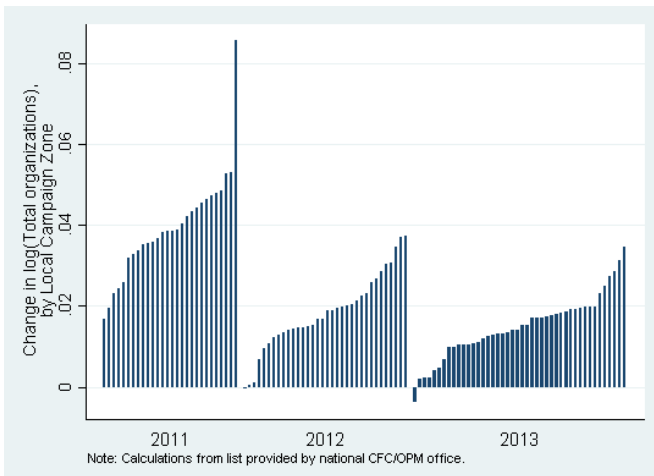
$$\log\left(GivingPerEmployee_{zy}\right) = \alpha + \beta_1 \log\left(Number_{zy}\right) + \beta_2 log\left(Employees_{zy}\right) + \boldsymbol{\beta_3}\, \boldsymbol{Demo_{zy}} + \boldsymbol{\beta_4 Economy_{zy}} + \gamma Zone + \delta Year + \epsilon_{zy}$$

To account for some non-linearities in the relationship between giving and number of employees (diminishing returns to scale), I control for log number of employees solicited on the right-hand-side of the equation. Demographic controls include measures for federal workforce composition at the market level, including gender composition, work status (proportion permanent & full-time), job type (proportion professional, proportion administrative), average salary, average length of service, average age, proportion military, and proportion postal service. Economic controls include per capita personal income, unemployment rates, population density, number of disasters, and disaster severity. The year fixed effects capture nationwide economic trends and any differences with how the CFC conducted the campaign from year to year. The zone fixed effects capture unobserved differences among zones/markets that persist over time, such as local generosity or traditions.[3] The resulting identifying variation comes from changes within a market over time and especially from the fact that entry into the national campaign (which is plausibly exogenous to local conditions) is perceived as a larger percentage increase in campaigns with small local lists. Figure 6 shows that substantial variation exists in the change in $\log(Number)$ over time.

[3] Time-varying local differences which are correlated with the number of nonprofits could affect this model, but most of these should be captured by the economic and demographic controls. Reverse causality (local nonprofits entering the zone because they anticipate an uptick in giving unrelated to the economy or worker characteristics) also cannot be accounted for with this model, although stories of this type assume a great deal of prescience on the part of nonprofit organizations, and are mitigated by the fact that most of my variation comes from the entry of nonprofits nationally, which is plausibly exogenous to local conditions, after controlling for year fixed effects.



(a)



(b)

Note: Year-over-year difference in log(Total Organizations) for (a) all local zones and (b) local zones in the individual data.

Figure 6. Variation in Dependent Variables

I analyze two additional dependent variables to further illuminate the relationship between the number of nonprofits in a market and giving—the participation rate and the average gift. The participation rate is the number of donors divided by the number of federal employees solicited in local geographic zone, and is therefore expressed as a proportion. This is the extensive margin. If the number of charities affects the participation rate, then non-donors are being converted to donors by the new options. The average gift is the total giving in a local geographic zone divided by the number of donors (giving per donor) or the average gift conditional on having given some amount $(\overline{g}_i | g_i > 0)$. This is the intensive margin. If the number of charities affects the average gift, then if all else is equal the donors are giving larger gifts (likely because of a better match between their interests and the charity's characteristics). The average gift and the participation rate are the two components of the giving per employee statistic.

$$\frac{Giving}{Employee} = \frac{Giving}{Donor} \times \frac{Donors}{Employee}$$

$$\text{Giving Per Employee } = \text{ Average Gift } \times \text{Participation Rate}$$

Next, I use the individual data to further investigate the relationship between the number of charities and giving by donors. All individual results will necessarily be investigating the average gift, since only donors are observed. The individual data is a powerful way of looking at this question, since I can include individual fixed effects to control for time-invariant characteristics of individuals, while also controlling for time-varying market characteristics. Using individual fixed effects means that changes to the compositions of federal workers or CFC donors cannot be driving my results. I estimate a log-log fixed effects model for individuals, *i*, taking part in a local administrative zone, *z*, in a given year, *y*. Because the total number of charities varies at the zone-year level, I cluster my standard errors at the zone level.

$$\log(Giving_{iy}) = \alpha + \beta_1 \log(Number_{zy}) + \beta_2 log\big(Employees_{zy}\big)$$

$$+ \boldsymbol{\beta_3\, Demo_{zy}} + \boldsymbol{\beta_4 Economy_{zy}} + \eta Individual_i + \delta Year_y + \epsilon_{iy}$$

I confirm results of both the aggregate and individual analyses using alternative functional forms. The primary among these is a linear form. The linear form includes the same control variables as the linear form and the same fixed effects.

$$GivingPerEmployee_{my}$$

$$= \alpha + \beta_1 Number_{my} + \boldsymbol{\beta_2 Demo_{my}} + \boldsymbol{\beta_3 Economy_{my}} + \gamma Market$$

$$+ \delta Year + \epsilon_{cy}$$

As an extension, I also examine how increases in the number of nonprofits within a subsector change the amount of giving directed to that subsector (vs. other subsectors). The logic is that donors may value new choices in some subsectors more than in others, either because the new nonprofits in some subsectors are more discernably different from preexisting organizations or because donors to these subsectors value variety more highly. To do so, I use the most well-known nonprofit classification scheme (NTEE codes) to divide nonprofits into 5 subsectors: Arts, Education, Health, Human Services, and Other (which includes environmental, international, and religious nonprofits, among others). Because of the large number of zeros in the subsector-level individual giving data (some donors only give to one subsector's nonprofits, leading to zeros in the data for their gifts to other subsectors), I use Tobit analyses to evaluate the effect.

As is typical in a tobit model, I am concerned with the underlying propensity of individual *i* to donate to local nonprofits (or the other dependent variables investigated) in year *y*. The tobit model acknowledges this propensity can be any real number ($-\infty$ to $+\infty$) and that if the propensity is in the negative range, the donated amount will be zero; otherwise the propensity will equal the true gift. Like in the OLS models estimated earlier, I include a full set of control variables and a normally distributed error term, ω_{iy}. The model includes individual-specific random effects η_i, which are i.i.d, $N\left(0, \sigma_\eta^2\right)$ and assumed to be independent of ω_{iy}, which are i.i.d, $N(0, \sigma_\omega^2)$.

$$PropGive_{iy} = \alpha + \beta_1 Number_{my} + \boldsymbol{\beta_2 Economy_{my}} + \boldsymbol{\beta_3 Economy_{my}} + \eta_i + \delta Year_y + \omega_{iy}$$

The model includes random effects rather than treating η as coefficients to be estimated. Not only would including fixed effects be computationally difficult, but a fixed effect model would also lead to biased estimates of β_1 and the other coefficients in the model.

1.7 Identification Challenges

The goal of this research is to identify the effect of the number of giving options on total giving (here, normalized as giving per employee). In research of this type, it is difficult to distinguish between locations that have more giving because they have more nonprofits and locations that have more nonprofits and more giving because they have characteristics that are valuable to both nonprofits and donors. To overcome this challenge, I use data that are longitudinal. Longitudinal data permits me to use of market (geographic zone) fixed effects, which control for the characteristics of the geographic zones, which remain constant over time. I am also able to control for observable economic characteristics at the level of the geographic zones.

A second challenge is unique to my data, which is specifically on giving by federal workers. Federal workers across all locations can be influenced by correlated shocks to their propensity to give because they may encounter similar pay changes or career stability concerns because they share an employer (the federal government). Therefore, I include year fixed effects to control for any policies or trends that affect federal workers as a whole. This is possible because the number of giving options (the number of eligible nonprofits) changes each year and varies by geographic zone. Furthermore, the composition of federal workers (and of donors) may have changed during this time period. With my aggregate data, I am able to control for characteristics of federal workers in a state and proportion of military and postal workers. Furthermore, because I have individual level data, I can include individual fixed effects. This separates the effect I observe from the changing composition of the federal workforce.

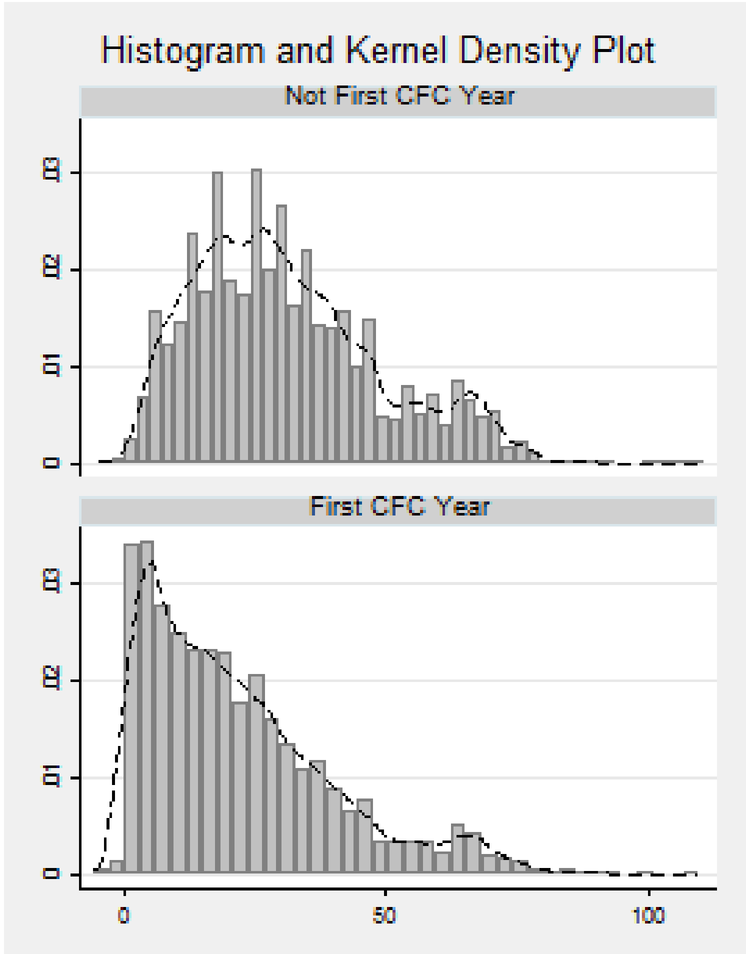
The remaining challenge to identification in the aggregate data is omitted variables that vary across time and differ by geographic zone. To bias my results, these characteristics would have to be correlated with both the number of nonprofit organizations participating in the CFC and the giving decisions of employees. Because nonprofits must apply to the CFC five to nine months before donations begin there is a built-in lag in the independent variable of interest. Therefore, any unobserved characteristic would need be serially correlated without being constant to pose a challenge to identification. For this to be an issue, nonprofits would need to be able to predict, either because of time trends or knowledge about coming changes to the federal workforce, what will happen in the CFC campaign in the coming year and decide whether or not to fill out the (free, relatively quick) application based on that knowledge.

The potential for endogeneity exists in all reduced form analyses of the effect of nonprofit options on total giving because, rather than being randomly assigned to enter a market, nonprofits choose to enter. Here, I take advantage of the fact that many nonprofit enter the CFC at a national level. National entry is plausibly unrelated to unobserved confounding variable, because a nonprofit's decision to enter nationally is unlikely to be driven by unobserved change in the performance of a local administrative zone. While local nonprofits also choose to enter the CFC, the major determinant of being included on a CFC choice list is a nonprofit's presence in a marketplace, which is unlikely to be decided based on ability of an organization to participate in the CFC in that market. Since the CFC plays a relatively minor role in the annual revenues of most nonprofits, the concerns about entry based on a relatively strong CFC year are more minimal. For nonprofits present within a market, entry cost is small, and typically consists of several hours devoted to filing the necessary paperwork. Figure 7 confirms that many of the new nonprofits in the CFC are young—they recently received 501(c)3 status from the IRS—especially when compared to previously-eligible organizations.

Ideally for identification the number of nonprofits participating in each geographic zone (or the change from the average in the geographic zone, in the case of our fixed effects model) would be random. A random change should not be predictable.

To see whether this is the case in the CFC data, I regress the change in nonprofit organizations from a geographic zone's average on the observed characteristics of the zone. When a log form is used (Table 7), there are no covariates that predict percent change in the number of nonprofits in the CFC, after including year and location fixed effects.

Regardless, without true randomization or a natural experiment that makes the number of organizations "as good as" random, there is still the potential for bias resulting from changes over time in the community that are not observed in my data. If that is the case, then it would make sense for these unobservable characteristics to be positively correlated with the number of participating organizations and giving. That is, organizations should be drawn to participate in the CFC if they believe giving is going to increase. If there is a bias, one would expect the direction to be positive; any positive coefficient would be overestimated.



Note: Years 2010 through 2013 are included. New organizations are defined as those appearing in any CFC geo- graphic zone for the first time, by federal tax ID (EIN). Therefore, organizations that expand to a new territoryare not considered new for the purposes of this figure only.

Figure 7. Ages of Organizations New to the CFC

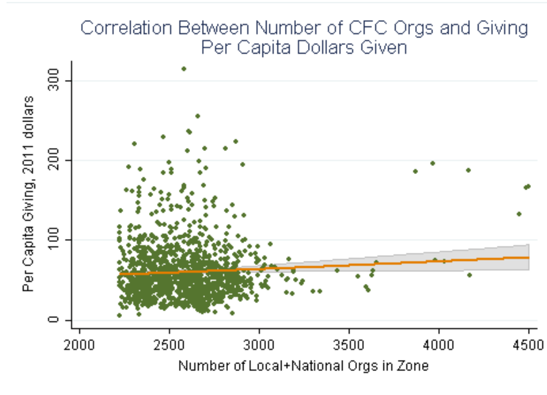
Table 7. What Predicts Change in log(Local Number of Charities)?

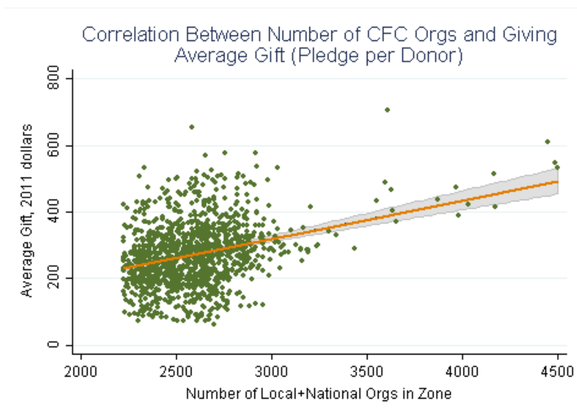
	DV: $\Delta log(TotalCharities)$
	(1)
log(Number Employees Solicited)	-0.000858
	(0.00446)
Per Capita Personal Income	0.000789
	(0.000983)
Unemployment Rate	-0.111
	(0.222)
Proportion Female	-0.430
	(0.394)
Proportion Permanent Status	-0.0209
	(0.157)
Proportion Professional Category	0.0167
	(0.429)
Proportion Administrative Category	-0.216
	(0.354)
Average Salary	0.000195
	(0.00300)
Average Length of Service	0.0249
	(0.0158)
Average Age	-0.0287
	(0.0159)
Proportion Postal Service	-0.00510
	(0.467)
Proportion Uniformed Military	-0.471
	(0.458)
Disaster Allocation (Sept-Dec)	-0.000000393
	(0.000000975)
Number of Disasters (Sept-Dec)	0.000884
	(0.000793)
Campaign FE	Yes
Year FE	Yes
Observations	537
Adjusted R^2	0.404

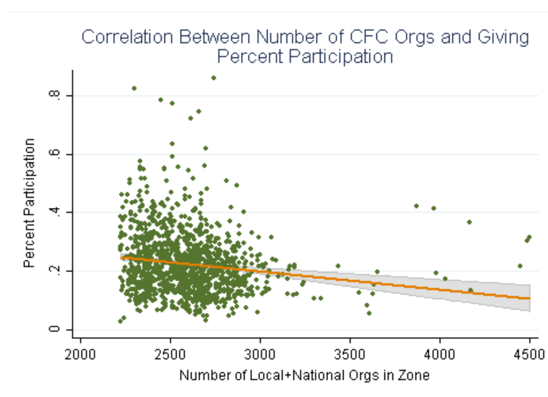
Note: Campaign years 2010-2013 are included. Disaster allocation is in millions of 2011 dollars. Average salary and per capita personal income are in thousands of 2011 dollars.

1.8 Main Findings

I begin here with a simple visual representation of the relationship between the total number of CFC charity options in a local geographic zone and the giving per capita within that zone. The scatter plot shown in Figure 8 pools the data across time. The graph shows a positive relationship between the variables of interest, total nonprofits and giving per capita through the CFC. The scatter plot shows a few outliers, which may be influencing this positive relationship. Likewise, the scatter plot showing the average giving and number of nonprofits over time shows a positive relationship. In contrast, there seems to be no relationship between participation and the number of nonprofits. These relationships do not include controls for local characteristics that may make a city hospitable to both nonprofit organizations and donors. Furthermore, they may be driven by the underlying time trends in the CFC rather than any causal relationship between the variables. Regression analysis is required to disentangle these issues.







Note: Years 2010-2013 are included.

Figure 8. Correlational Plots for Number of Organizations in a Zone and Dependent Variables

1.8.1 Aggregate data with market and year fixed effects

Table 8 examines the relationship between the number of charities in the CFC and per employee pledges. If there is an increase in pledges per employee (giving per capita) when the number of charities increases, then this is showing that the total amount donated increases when the number of charities increases. The first model (1), which controls only for the size of a campaign, indicates a significant and positive relationship between nonprofit options and giving. This positive effect persists even after controlling for economic factors (2), demographic and professional characteristics of the employees within the zone (3), disasters during the campaign period (4), and nonlinear versions of these variables (5). The model with year fixed effects (6) identifies the relationship between nonprofit options and giving mainly using persistent effects across regions and shows a large positive effect; this indicates the importance of unobserved differences between regions and highlights the usefulness of the longitudinal data here. The preferred model (7) controls for persistent differences between CFC local administrative zones. This model shows a positive, but insignificant, effect – it cannot be distinguished from zero. In other words, although regions with a large number of nonprofits participating also tend to have high levels of giving, there is no evidence that increasing the number of charities within a region over time increases giving through the CFC. Table 9 shows that this finding does not change when using a linear functional form.

Table 10 shows the results for the intensive and extensive margins of giving, respectively. Columns (1) and (3) examine the change in average giving or giving per

Table 8. Main Results: Log(Per Capita Giving) and Log(Total Charities)

	DV: log(Pledges per Employee)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Basic	Econ Controls	Demo Controls	Disaster Controls	Non-linear Controls	Year FE	Zone FE
log(Local+Natl Org Count)	1.834***	2.157***	1.898***	1.910***	1.936***	4.303***	0.00676
	(0.492)	(0.535)	(0.554)	(0.556)	(0.561)	(0.659)	(0.390)
log(Number Employees Solicited)	-0.111**	-0.116***	-0.121**	-0.122**	-0.129***	-0.170***	-0.893***
	(0.0338)	(0.0343)	(0.0369)	(0.0369)	(0.0376)	(0.0391)	(0.0542)
Per Capita Personal Income		-0.00529	0.00397	0.00410	0.00615	-0.000124	-0.00117
		(0.00591)	(0.00680)	(0.00683)	(0.00705)	(0.00703)	(0.00676)
Unemployment Rate		1.680	3.915*	3.897*	14.24	2.271	6.050
		(1.659)	(1.962)	(1.955)	(8.417)	(7.579)	(4.103)
Proportion Female			-0.230	-0.226	-0.272	-2.735*	0.266
			(1.185)	(1.191)	(1.203)	(1.285)	(2.654)
Proportion Permanent Status			2.079	2.131	2.100	3.050*	-1.013
			(1.362)	(1.371)	(1.390)	(1.365)	(0.881)
Proportion Professional Category			-0.00318	-0.122	0.166	2.990*	0.145
			(1.478)	(1.460)	(1.478)	(1.489)	(2.560)
Proportion Administrative Category			0.432	0.372	0.731	1.903	2.662
			(1.303)	(1.312)	(1.333)	(1.328)	(1.821)
Average Salary			-0.00388	-0.00301	-0.00679	-0.0362**	-0.00960
			(0.0117)	(0.0115)	(0.0118)	(0.0121)	(0.00923)
Average Length of Service			-0.0210	-0.0240	-0.0245	-0.0820	-0.0812
			(0.0550)	(0.0551)	(0.0555)	(0.0561)	(0.0597)
Average Age			-0.00428	-0.00444	-0.0307	0.144*	0.110
			(0.0640)	(0.0640)	(0.0656)	(0.0683)	(0.0873)
Proportion Postal Service			-1.444*	-1.426*	-1.508*	-0.608	-0.0552
			(0.586)	(0.584)	(0.597)	(0.581)	(1.271)
Proportion Uniformed Military			-0.602	-0.600	-0.572	-0.377	0.0987
			(0.383)	(0.383)	(0.387)	(0.379)	(1.135)

Disaster Allocation (Sept-Dec)				-0.00000786	-0.0000136	-0.00000146	-0.00000744
				(0.0000226)	(0.0000226)	(0.0000196)	(0.00000588)
Number Disasters (Sep-Dec)				-0.00158	0.00204	0.00429	-0.00161
				(0.0141)	(0.0139)	(0.0133)	(0.00496)
Unemployment Rate × Unemployment Rate					-55.51	-4.276	-23.74
					(44.18)	(37.87)	(20.22)
Zone FE	No	No	No	No	No	No	Yes
Year FE	No	No	No	No	No	Yes	Yes
Observations	744	744	744	744	744	744	744
Adjusted R^2	0.057	0.065	0.090	0.088	0.092	0.228	0.964

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at the local campaign zone level and adjusted for clusters. Campaign years 2010-2013 are included. Disaster allocation is in millions of 2011 dollars. Average salary and per capita personal income are in thousands of 2011 dollars.

Table 9. Alternative Functional Form, Linear Per Capita Giving

	DV: Per Cap Gift (2011 dollars)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Basic	Controls 1	Controls 2	Controls 3	YearFE	ID+FE
Local+National Org Count	0.0104	0.0189	0.0118	0.0134	0.0447**	0.00817
	(0.00856)	(0.0101)	(0.0123)	(0.0122)	(0.0148)	(0.0115)
Number Employees Solicited	0.0000442	0.0000439	0.0000304	0.0000237	-0.0000641	-0.00163***
	(0.000129)	(0.000136)	(0.000136)	(0.000133)	(0.000124)	(0.000417)
Per Capita Personal Income		-0.672	-0.00992	0.137	-0.142	0.152
		(0.463)	(0.530)	(0.528)	(0.529)	(1.004)
Unemployment Rate		40.26	196.5	254.3	-210.0	1050.5
		(99.21)	(131.7)	(437.7)	(412.1)	(588.2)
Proportion Female			17.57	41.54	-57.98	131.3
			(85.46)	(84.96)	(88.07)	(366.7)
Proportion Permanent Status			117.2	123.0	147.7	6.497
			(88.42)	(87.58)	(90.42)	(93.95)
Proportion Professional Category			-15.80	-25.85	84.54	-21.29
			(103.8)	(101.3)	(106.1)	(307.3)
Proportion Administrative Category			25.35	-9.136	47.15	53.35
			(84.60)	(81.58)	(82.52)	(215.9)
Average Salary			-0.288	0.116	-1.092	0.748
			(0.793)	(0.762)	(0.796)	(0.740)
Average Length of Service			-0.458	-0.368	-1.975	-7.772
			(3.420)	(3.283)	(3.525)	(5.505)
Average Age			2.029	1.003	7.752	-1.103
			(4.256)	(4.298)	(4.653)	(8.210)
Proportion Postal Service			-93.80**	-87.31*	-54.73	-58.62
			(36.04)	(36.14)	(35.53)	(137.8)
Proportion Uniformed Military			-46.18*	-42.36	-33.75	77.72
			(22.23)	(22.09)	(21.71)	(148.7)
Unemployment Rate × Unemployment Rate				-265.8	1654.3	-4587.6*
				(2393.2)	(2207.6)	(2286.1)
Disaster Allocation (Sept-Dec)				-0.00203	-0.00120	-0.000196
				(0.00127)	(0.00131)	(0.000630)

	(1)	(2)	(3)	(4)	(5)	(6)
Number Disasters (Sep-Dec)				-7.886***	-5.979***	-0.659
				(1.656)	(1.614)	(0.913)
Number Disasters (Sep-Dec) × Number Disasters (Sep-Dec)				1.062***	0.822***	0.0616
				(0.209)	(0.218)	(0.119)
Zone FE	No	No	No	No	No	Yes
Year FE	No	No	No	No	Yes	Yes
Observations	744	744	744	744	744	744
Adjusted R^2	0.006	0.019	0.038	0.063	0.105	0.898

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at the local campaign zone level and adjusted for clusters. Campaign years 2010-2013 are included. Disaster allocation is in millions of 2011 dollars. Average salary and per capita personal income are in thousands of 2011 dollars.

donor. With the proper controls, the linear form shows a statistically significant and positive result. In other words, I find that current donors increase their giving when the number of nonprofits in the CFC increases. The point estimate is $0.07 cents of increased contributions per donor. Average gifts range from $257 to $311 dollars over this time period, so this is a very small increase. The log-log model also produces positive results, but in this case they are statistically insignificant.

Columns (2) and (4) examine how participation in the CFC (giving any amount) is related to the number of nonprofit organizations. Participation is measured as donors per employee solicited, a proportion. The two models do not show a statistically significant relationship between the number of nonprofits and participation in the CFC. In fact, the point estimate for the log-log model is negative, which might be consistent with a negative reaction to an exceptionally long list of nonprofit options.

Table 10. Intensive and Extensive Margins, Aggregate Data

	Log-Log Models		Linear Models	
	(1)	(2)	(3)	(4)
	log(Pledges Per Donor)	log(Participation)	Pledges Per Donor	Participation Rate
log(Local+Natl Org Count)	0.330	-0.323		
	(0.251)	(0.530)		
Local+National Org Count			0.0699***	0.0000734
			(0.0185)	(0.0000725)
Number Employees Solicited			-0.000289	-0.00000732**
			(0.000471)	(0.00000236)
log(Number Employees Solicited)	-0.0499	-0.843***		
	(0.0480)	(0.0776)		
Per Capita Personal Income	-0.00406	0.00289	-1.127	0.00103
	(0.00559)	(0.00770)	(1.801)	(0.00306)
Unemployment Rate	0.951	5.099	211.4	1.545
	(3.635)	(5.704)	(1221.5)	(1.559)
Unemployment Rate × Unemployment Rate	-12.19	-11.56	-1697.6	-4.581
	(16.38)	(26.34)	(5340.5)	(5.988)
Proportion Female	-4.419	4.685	-1543.2*	1.592
	(2.308)	(3.451)	(690.7)	(1.365)
Proportion Permanent Status	0.245	-1.258	77.63	-0.108
	(0.820)	(1.181)	(250.1)	(0.283)
Proportion Professional Category	3.794	-3.649	1579.6*	-0.624
	(2.026)	(3.220)	(631.7)	(0.947)
Proportion Administrative Category	0.975	1.686	364.4	1.190
	(2.032)	(2.839)	(621.3)	(0.966)
Average Salary	-0.00654	-0.00306	-2.740	0.00316
	(0.00945)	(0.0131)	(3.197)	(0.00297)
Average Length of Service	-0.00780	-0.0734	-0.291	-0.0255
	(0.0338)	(0.0663)	(10.04)	(0.0231)
Average Age	0.0318	0.0782	14.05	-0.0308
	(0.0719)	(0.115)	(20.12)	(0.0386)
Proportion Postal Service	1.299	-1.354	211.9	-0.676
	(0.978)	(1.661)	(264.7)	(0.516)
Proportion Uniformed Military	-0.775	0.873	-244.0	0.673
	(1.064)	(1.630)	(338.3)	(0.715)
Disaster Allocation (Sept-Dec)	0.00000215	-0.00000959	-0.000498	0.000000335
	(0.00000631)	(0.00000893)	(0.00179)	(0.00000291)
Number Disasters (Sep-Dec)	0.00138	-0.00299	-3.579	-0.00341
	(0.00400)	(0.00664)	(2.550)	(0.00346)
Number Disasters (Sep-Dec) × Number			0.485*	0.000156
			(0.247)	(0.000409)
Zone FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	744	744	744	744
Adjusted R^2	0.943	0.907	0.924	0.812

Note: * p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors clustered at the local campaign zone level and adjusted for clusters. Campaign years 2010-2013 are included. Disaster allocation is in millions of 2011 dollars. Average salary and per capita personal income are in thousands of 2011 dollars.

1.8.2 Individual data with employee fixed effects

The individual giving data are important to this study, as they provide a means of testing the robustness of the aggregate data results to individual fixed effects. By using individual fixed effects, I avoid issues of selection, which may make the relationship between average giving and the number of organizations in a market difficult to interpret.

In contrast to the aggregate results, I do not find a relationship between average giving and the number of nonprofits in the market when using the individual data. Table 11 shows a positive but insignificant relationship using both log-log and linear functional forms. While log-log model (1) shows a significant positive relationship (it replicates the correlational scatter plot from figure 8), this relationship disappears after including control variables (2), fixed effects (3), or both (4), with the latter showing a 0.08 percent increase in donations for a 1 percent increase in nonprofit options. All of the linear form results (5-8) show insignificant relationships; the preferred linear model (8) estimates that each new nonprofit organization increases giving by $0.03 per donor. The use of individual fixed effects means that this result is specifically for those individuals who participate through the Nexus online giving system in multiple years.

Table 12 shows that including individual fixed effects is important to the results, as zone fixed effects lead to both a large standard error and an illogical point estimate, especially in the log-log functional form.

Table 11. Individual Main Results, Both Functional Forms

	DV: Log(Pledges Per Donor)				DV: Pledges Per Donor			
	(1) Basic	(2) Controls	(3) FE	(4) FE + Controls	(5) Basic	(6) Controls	(7) FE	(8) FE + Controls
log(Local+Natl Org Count)	1.182*	0.633	0.0451	0.0774				
	(0.463)	(0.590)	(0.315)	(0.259)				
log(Number Solicited Employees)	-0.120	-0.129	-0.0147	-0.0194				
	(0.0725)	(0.0707)	(0.0251)	(0.0228)				
Local+National Org Count					0.0807	0.0848	-0.00504	0.0311
					(0.0417)	(0.0496)	(0.0630)	(0.0515)
NumSolicit (Mean)					0.000197	-0.000537**	0.000156	-0.0000586
					(0.000196)	(0.000198)	(0.000593)	(0.000595)
Per Capita Personal Income		0.00167		-0.00385		6.984***		-2.520
		(0.00743)		(0.00248)		(1.936)		(1.378)
Unemployment Rate		-3.824		0.940		5607.3		1391.5
		(2.356)		(1.798)		(3372.0)		(1635.1)
Proportion Female		-3.613*		0.0523		-685.1		315.9
		(1.717)		(1.157)		(394.2)		(757.5)
Proportion Permanent Status		2.583		0.194		1234.1**		-136.0
		(1.365)		(0.380)		(469.2)		(180.5)
Proportion Professional Category		0.300		-0.423		8085.7***		-5715.2*
		(2.103)		(0.891)		(2246.1)		(2683.4)
Proportion Administrative Category		-0.419		-0.0526		-110.0		-345.0
		(1.507)		(0.750)		(432.0)		(400.3)
Average Salary		0.0143		-0.00228		2.887		1.290
		(0.0192)		(0.00362)		(5.419)		(2.979)
Average Length of Service		-0.0431		0.0267		-5.659		19.93
		(0.0713)		(0.0362)		(18.45)		(20.74)
Average Age		-0.108		-0.00353		-41.50		3.148
		(0.0762)		(0.0523)		(24.84)		(22.42)
Proportion Postal Service		0.377		-0.539		-163.4		212.3
		(0.778)		(0.714)		(218.7)		(500.6)
Proportion Uniformed Military		-0.368		-0.196		-40.56		-158.2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		(0.586)		(0.332)		(141.9)		(147.9)
Disaster Allocation (Sept-Dec)		-0.0000503		-0.000000996		-0.0107		-0.00500
		(0.0000371)		(0.00000527)		(0.00927)		(0.00383)
Number of Disasters (Sept-Dec)		0.0189		0.0000263		-19.70		-1.577
		(0.0191)		(0.00324)		(13.45)		(4.417)
Unemployment Rate × Unemployment Rate						-36110.0		-6906.8
						(20711.5)		(8101.9)
Proportion Professional Category × Proportion Professional Category						-14563.8***		9358.2
						(4204.3)		(4774.0)
Number of Disasters (Sept-Dec) × Number of Disasters (Sept-Dec)						3.550*		0.366
						(1.641)		(0.602)
Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Individual FE	No	No	Yes	Yes	No	No	Yes	Yes
Observations	201971	201971	201971	201971	201971	201971	201971	201971
Adjusted R^2	0.012	0.027	0.939	0.939	0.011	0.019	0.911	0.911

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at the local campaign zone level and adjusted for clusters. Campaign years 2010-2013 are included. Disaster allocation is in millions of 2011 dollars. Average salary and per capita personal income are in thousands of 2011 dollars.

Table 12. Individual Main Results, Both Functional Forms

	DV: Log(Pledges Per Donor)		DV: Pledges Per Donor	
	(1) Zone FE	(2) Indiv FE	(3) Zone FE	(4) Indiv FE
log(Local+Natl Org Count)	-2.117	0.0774		
	(1.084)	(0.259)		
log(Number Solicited Employees)	0.181	-0.0194		
	(0.164)	(0.0228)		
Local+National Org Count			-0.112	0.0311
			(0.0866)	(0.0515)
(mean) NumSolicit			0.000750	-0.0000586
			(0.000766)	(0.000595)
Per Capita Personal Income	0.0140	-0.00385	3.234	-2.520
	(0.0101)	(0.00248)	(4.967)	(1.378)
Unemployment Rate	-9.310***	0.940	488.3	1391.5
	(2.199)	(1.798)	(2831.6)	(1635.1)
Proportion Female	5.106	0.0523	1512.6	315.9
	(6.151)	(1.157)	(1483.1)	(757.5)
Proportion Permanent Status	-3.104**	0.194	-426.2	-136.0
	(1.062)	(0.380)	(303.1)	(180.5)
Proportion Professional Category	3.975	-0.423	-1111.4	-5715.2*
	(6.212)	(0.891)	(5080.8)	(2683.4)
Proportion Administrative Category	4.178	-0.0526	957.2	-345.0
	(5.335)	(0.750)	(1495.3)	(400.3)
Average Salary	0.000174	-0.00228	0.785	1.290
	(0.0213)	(0.00362)	(5.695)	(2.979)
Average Length of Service	-0.224***	0.0267	-17.27	19.93
	(0.0626)	(0.0362)	(21.54)	(20.74)
Average Age	0.244*	-0.00353	7.896	3.148
	(0.108)	(0.0523)	(33.69)	(22.42)
Proportion Postal Service	1.692	-0.539	869.0	212.3
	(2.741)	(0.714)	(1089.6)	(500.6)
Proportion Uniformed Military	2.399	-0.196	798.3	-158.2
	(2.169)	(0.332)	(748.3)	(147.9)
Disaster Allocation (Sept-Dec)	-0.0000757**	-0.000000996	-0.00160	-0.00500
	(0.0000254)	(0.00000527)	(0.00561)	(0.00383)
Number of Disasters (Sept-Dec)	0.0237*	0.0000263	18.77***	-1.577
	(0.0101)	(0.00324)	(5.335)	(4.417)
Unemployment Rate × Unemployment Rate			-9765.2	-6906.8
			(14198.0)	(8101.9)
Proportion Professional Category × Proportion Professional Category			510.9	9358.2
			(8047.3)	(4774.0)
Number of Disasters (Sept-Dec) × Number of Disasters (Sept-Dec)			-2.108**	0.366
			(0.798)	(0.602)
Year FE	Yes	Yes	Yes	Yes
Zone FE	Yes	No	Yes	No
Individual FE	No	Yes	No	Yes
Observations	201971.000	201971.000	201971.000	201971.000
Adjusted R^2	0.077	0.939	0.032	0.911

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at the local campaign zone level and adjusted for clusters. Campaign years 2010-2013 are included. Disaster allocation is in millions of 2011 dollars. Average salary and per capita personal income are in thousands of 2011 dollars.

1.8.3 Heterogeneity analyses

While these results show that there is no economically significant increase in giving as new nonprofits enter the CFC campaigns, it is possible that employees' responsiveness to the number of nonprofit organizations may differ depending on characteristics of the geographic zone or characteristics of individual donors. I analyze whether responses vary by four characteristics of the geographic zone and three individual characteristics. The four campaign characteristics are: number of nonprofits, number of employees, urbanness (measured by density and presence of a major metropolitan city), and region (measured as the 4 census regions). The three individual characteristics are military service, gender (which is only available for non-military individuals), and urbanness of place of work. I test heterogeneous effects in both the aggregate and individual giving data. For the continuous measures (number, number of employees, density, proportion female, and proportion military), I test both indicator variables for high and low values of the variable (splitting at approximately the sample median) and continuous versions of the variable. I employ both interactions with the "number of nonprofits" variable of interest and split sample specifications, while continuing to include the main model control variables and fixed effects for year and market.

Table 13 indicates that the relationship between the number of charities and per capita giving is not different based on the subgroups analyzed. The majority of the relationships tested in Tables 14-16 are likewise insignificant. The one exception is campaigns with a high proportion military. Table 14 demonstrates that campaigns where a high proportion of the employees are military experience an average gift decrease compared to campaigns with a low proportion of military employees. This is the case both when looking at a continuous measure of proportion military (row 4) and when looking at a binary indicator for “high” proportion military. The magnitude of the effect is large. For those campaigns with a low military proportion, a 1 percent increase in organizations leads to a 1 percent increase in average gift size; for those with a high military proportion, there is a 0.04 percent increase. Table 15 indicates that the reason for this decrease in gift size may be an increase in participation, although this is only significant when examining the continuous variable (row 4) not the indicator variable (row 10), which has a similar sign but is insignificant. Table 16, the heterogeneity analysis for the individual data, shows that average gift sizes do not change once I control for selection of individual into donating (through individual fixed effects). Looking especially at row 11, one can see that it is not that existing donors who are part of the military behave differently than civilian donors to an increase in nonprofit options. Taken together these results show that more organizations cause an increase in small gifts by military members who might not have given otherwise, driving down per-donor giving for this subgroup.

Table 13. Aggregate Heterogeneity, LogPerCapPledges, LogTotalCharities

	Coef	SE	Pvalue	SplitFTest	SplitCoef	SplitSE	Pvalue
LocalC							
logCharities	-8.583048	23.61223	.7165234	.	.	.	.
logCharities*logCharities	.5337703	1.465888	.7160553	.	.	.	.
EmployeesC							
logCharities	-.0218458	.3858865	.9548973	.	.	.	.
logCharities*NumSolicit	3.58e-07	3.90e-07	.3586356	.	.	.	.
DensityC							
logCharities	.0152847	.4000561	.969552	.	.	.	.
logCharities*PD weighted	6.82e-06	6.01e-06	.2572372	.	.	.	.
MilitaryC							
logCharities	-.5247322	.8056144	.5153932	.	.	.	.
logCharities*pct militaryC	1.475001	1.788077	.4101705	.	.	.	.
FemaleC							
logCharities	-1.779317	2.276704	.4351927	.	.	.	.
logCharities*pct femaleC	4.307218	5.496653	.4339755	.	.	.	.
LocalI							
logCharities	-.2487926	.6447612	.6999065	.6564	.	.	.
logCharities*LotsLocal	.3049867	.5527801	.5816001	.	.	.	.
EmployeesI							
logCharities	-.302488	.6135154	.6223953	.9567	.	.	.
logCharities*BigRegion	.348997	.5083919	.4930201	.	.	.	.
DensityI							
logCharities	-.06911	.6073148	.9094864	.9283	.	.	.
logCharities*MostDense	.1049669	.4834361	.8282778	.	.	.	.

DensityI2							
logCharities	-.1867321	.6001933	.7559558	.7556	.	.	.
logCharities*BigCity	.2630472	.5423518	.6280714	.	.	.	.
MilitaryI							
logCharities	.0025785	.6065948	.9966116	.7092	.	.	.
logCharities*LotsMilitary	.0052852	.5451161	.9922716	.	.	.	.
FemaleI							
logCharities	.0116498	.3945402	.9764663	.465	.	.	.
logCharities*LotsFemale	-.0281523	.4707459	.9523575	.	.	.	.
Region							
logCharities	-.8292285	1.031252	.4220662	.0026	.2908882	2.503026	.9080364
logCharities*Midwest	.0252075	1.106254	.981838	.	.6256225	2.290419	.786181
logCharities*South	.9610347	.958288	.3168472	.	-.5457656	.4453382	.2226517
logCharities*West	.4047831	.92731	.6628225	.	1.590305	1.866347	.398069

Table 14. Aggregate Heterogeneity, LogPerDonorPledges, LogTotalCharities

	Coef	SE	Pvalue	SplitFTest	SplitCoef	SplitSE	Pvalue
LocalC							
logCharities	-22.03566	15.20072	.1483488	.	.	.	.
logCharities*logCharities	1.38979	.9393297	.1401888	.	.	.	.
EmployeesC							
logCharities	.3441625	.2473419	.1652665	.	.	.	.
logCharities*NumSolicit	-1.80e-07	2.49e-07	.4722233	.	.	.	.
DensityC							
logCharities	.3358446	.2456119	.172674	.	.	.	.
logCharities*PD weighted	4.81e-06	5.15e-06	.3511675	.	.	.	.
MilitaryC							
logCharities	1.148798	.5272733	.030238	.	.	.	.
logCharities*pct militaryC	-2.272789	1.114724	.0424619	.	.	.	.
FemaleC							
logCharities	-.7836321	1.749147	.6545161	.	.	.	.
logCharities*pct femaleC	2.685172	4.189761	.5221528	.	.	.	.
LocalI							
logCharities	.2427783	.3811859	.5247422	.4472	.	.	.
logCharities*LotsLocal	.103892	.3183848	.7444497	.	.	.	.
EmployeesI							
logCharities	.1688642	.3570074	.6366062	.4715	.	.	.
logCharities*BigRegion	.1816558	.30748	.5551692	.	.	.	.
DensityI							
logCharities	.0548271	.3661047	.8810704	.6832	.	.	.

logCharities*MostDense	.3804565	.3384284	.2619591	.	.	.	.
DensityI2							
logCharities	.2170641	.3384461	.5218506	.9642	.	.	.
logCharities*BigCity	.1533022	.3007254	.6106367	.	.	.	.
MilitaryI							
logCharities	1.072347	.4821007	.026976	.1129	.	.	.
logCharities*LotsMilitary	-.9377941	.3758309	.0132002	.	.	.	.
FemaleI							
logCharities	.2668589	.2910991	.3601247	.6779	.	.	.
logCharities*LotsFemale	.3627912	.3348654	.2796258	.	.	.	.
Region							
logCharities	.6762097	.7815528	.3877104	.0889	.	.	.
logCharities*Midwest	-.5117713	.7961765	.5209228	.	.	.	.
logCharities*South	-.295681	.7374268	.6887728	.	.	.	.
logCharities*West	-.6514482	.7335426	.3753065	.	.	.	.

Table 15. Aggregate Heterogeneity LogPctParticipate, LogTotalCharities

	Coef	SE	Pvalue	SplitFTest	SplitCoef	SplitSE	Pvalue
LocalC							
logCharities	13.45256	25.73636	.6016186	.	.	.	.
logCharities*logCharities	-.8560168	1.592252	.5912983	.	.	.	.
EmployeesC							
logCharities	-.3660084	.5220782	.4838851	.	.	.	.
logCharities*NumSolicit	5.38e-07	5.71e-07	.3468786	.	.	.	.
DensityC							
logCharities	-.3205599	.5361044	.5503925	.	.	.	.
logCharities*PD weighted	2.01e-06	7.05e-06	.7760169	.	.	.	.
MilitaryC							
logCharities	-1.67353	1.035935	.1074064	.	.	.	.
logCharities*pct militaryC	3.747789	2.106335	.0763465	.	.	.	.
FemaleC							
logCharities	-.9956857	2.53539	.694848	.	.	.	.
logCharities*pct femaleC	1.622048	5.949197	.7853363	.	.	.	.
LocalI							
logCharities	-.4915716	.799802	.5393393	.2216	.	.	.
logCharities*LotsLocal	.2010954	.6434996	.7549062	.	.	.	.
EmployeesI							
logCharities	-.4713527	.771885	.5419577	.6795	.	.	.
logCharities*BigRegion	.1673416	.5983678	.7799555	.	.	.	.
DensityI							
logCharities	-.1239373	.7138245	.8622942	.9153	.	.	.
logCharities*MostDense	-.2754894	.5830355	.6369555	.	.	.	.

DensityI2							
logCharities	-.4037968	.7189222	.5748195	.787	.	.	.
logCharities*BigCity	.1097455	.621755	.8600297	.	.	.	.
MilitaryI							
logCharities	-1.069768	.8762368	.2232298	.8818	.	.	.
logCharities*LotsMilitary	.9430793	.6623838	.1556996	.	.	.	.
FemaleI							
logCharities	-.2552093	.5871119	.6641469	.1272	.	.	.
logCharities*LotsFemale	-.3909432	.54559	.4742868	.	.	.	.
Region							
logCharities	-1.505438	1.546395	.3311923	.011	-.2789504	3.75069	.9410666
logCharities*Midwest	.5369779	1.510848	.7225637	.	.0650058	3.855848	.986635
logCharities*South	1.256715	1.40889	.3732139	.	-.8690049	.5009176	.0851976
logCharities*West	1.056231	1.341906	.4319249	.	.4325148	2.271267	.8497146

Table 16. Individual Heterogeneity, log(TotalPledge), Log(TotalCharities)

	Coef	SE	Pvalue	SplitFTest	SplitCoef	SplitSE	Pvalue
LocalC							
logCharities	2.026854	14.68015	.8904702	.	.	.	.
logCharities*logChariti	-.119671	.9038149	.8949342	.	.	.	.
EmployeesC							
logCharities	.0435205	.2742686	.8742488	.	.	.	.
logCharities*NumSolici	8.22e-08	1.49e-07	.5821549	.	.	.	.
DensityC							
logCharities	.0754078	.2615363	.7737058	.	.	.	.
logCharities*PD	3.28e-07	2.74e-06	.9049493	.	.	.	.
MilitaryC							
NumLcoal	-.0551472	.41747	.8951771	.	.	.	.
logCharities*pct	.6827186	1.268857	.5917569	.	.	.	.
FemaleC							
logCharities	-.3026195	1.551092	.8457178	.	.	.	.
logCharities*pct	.9428021	3.736742	.801333	.	.	.	.
LocalI							
logCharities	.0488812	.2695674	.8564815	0	23.22877	2.830993	3.99e-07
logCharities*LotsLocal	.0048982	.0035995	.176693	.	.1326119	.2854638	.6435009
EmployeesI							
logCharities	.0986666	.2449543	.6879758	0	0	0	.
logCharities*BigRegion	-.0076375	.0053277	.1548854	.	.1135571	.2904343	.6967282
DensityI							
logCharities	.0024849	.2966913	.9933346	.1129	.	.	.
logCharities*MostDens	.0042842	.0032439	.1896745	.	.	.	.
DensityI2							
logCharities	.0779178	.2573744	.7627288	.0273	.4557419	1.542099	.7697669
logCharities*BigCity	-.00052	.0041575	.9007197	.	.2570859	.2976353	.3907116
MilitaryI							
logCharities	.1117306	.25167	.6580527	.6544	.	.	.
logCharities*LotsMilita	.0075209	.0045942	.1048315	.	.	.	.
MilitaryIndiv							
logCharities	.008192	.6918434	.9905791	.0983	.	.	.
logCharities*LotsMilita	.0069874	.0229056	.7610382	.	.	.	.
FemaleI							
logCharities	.0536322	.269716	.8427943	.0079	-.3922589	.6080853	.52223
logCharities*LotsFemal	-.0036356	.0059573	.5430976	.	.3268705	.2907573	.2659925
FemaleIndiv							
logCharities	-.2638811	.4174429	.5289179	.3311	.	.	.
logCharities*LotsFemal	.0002361	.0141332	.9867113	.	.	.	.

Region							
logCharities	-.2653907	.4073629	.5162586	.	-.6217652	.5592111	.2837012
logCharities*Midwest	.0092048	.633814	.9884424	.	-.876388	1.094747	.4367733
logCharities*South	.3508038	.4739095	.4609278	.	.4210417	.9377605	.6559266
logCharities*West	.3510753	.4708075	.4576411	.	-.4971857	.9012743	.5857271

1.8.4 Subsector extension

Table 17 examines whether the effect of adding nonprofit options differs by charitable subsector using a Tobit model. The presented results are marginal effects on the uncensored observations, which can be thought of as an effect on the intensive margin (pledge per donor or average gift). I find that a 1 percent increase in the number of arts and culture organizations leads to a .49 percent increase in the average gift to this subsector; a 1 percent increase in education organization increases average gifts to education by .41 percent. This can be interpreted as a decrease in the per-charity gift, since giving is not rising proportionally with the number of organizations in the market. This is especially true for health organizations, which show a .06 percent increase. In contrast, donors appear to be very responsive to new human services and “other” organizations (which include international, environment, and religious organizations, among other categories). In both of these cases, increasing organizations by 1 percent increased giving by over 1 percent (1.18 percent for human services and 1.13 percent for other). It should be noted that the results presented here use individual random effects, not fixed effects, and so comparison between this table and previous results is not direct.

Table 17. Log-log Tobit Results for 5 Subsectors, Individual Data

	DV: log(Giving to Organizations)				
	(1) AR	(2) ED	(3) HE	(4) HU	(5) OT
log(Arts Culture Total Orgs)	0.493***				
	(13.52)				
log(Education Total Orgs)		0.412***			
		(11.74)			
log(Health Total Orgs)			0.0610		
			(0.41)		
log(Human Services Total Orgs)				1.182***	
				(15.13)	
log(Other Total Orgs)					1.256***
					(4.49)
log(Solicited Employees)	-0.0226***	0.00381	0.0174	-0.230***	-0.134***
	(-4.02)	(0.51)	(1.22)	(-15.01)	(-8.30)
Per Capita Personal Income	0.00233***	0.00425***	-0.00664***	0.00767***	0.0109***
	(3.96)	(5.47)	(-5.08)	(5.48)	(7.02)
Unemployment Rate	-0.240	1.675***	-5.599***	-2.951***	1.882**
	(-1.03)	(5.94)	(-9.92)	(-5.11)	(3.19)
Proportion Female	-1.032***	-0.825***	-1.887***	-4.035***	-2.347***
	(-8.44)	(-5.70)	(-6.54)	(-13.41)	(-7.82)
Proportion Permanent Status	1.094***	2.236***	0.421	4.538***	0.287
	(7.88)	(13.15)	(1.23)	(13.01)	(0.82)
Proportion Professional Category	0.512**	1.461***	0.496	0.370	0.779
	(3.16)	(7.60)	(1.28)	(0.93)	(1.93)
Proportion Administrative Category	0.133	0.713***	0.0270	1.250***	-0.750*
	(1.08)	(4.84)	(0.09)	(4.14)	(-2.42)
Average Salary	-0.00563***	-0.0111***	-0.000554	-0.00615	0.0192***
	(-4.16)	(-6.80)	(-0.17)	(-1.81)	(5.62)
Average Length of Service	0.00997	0.0150	0.0729***	-0.0254	-
	(1.47)	(1.80)	(4.43)	(-1.51)	(-4.51)
Average Age	-0.00821	-0.0418***	-0.101***	-0.145***	-0.00255
	(-0.97)	(-4.19)	(-5.04)	(-7.08)	(-0.12)
Proportion Postal Service	0.399***	0.354***	0.115	1.343***	0.536**
	(5.12)	(3.50)	(0.71)	(7.36)	(2.78)
Proportion Uniformed Military	0.261***	0.230***	-0.236*	0.353**	0.100
	(6.16)	(3.96)	(-2.27)	(2.99)	(0.85)
Disaster Allocation (Sept-Dec)	0.0000164***	0.00000125	-0.0000164	-0.0000297**	-0.0000178
	(4.38)	(0.27)	(-1.84)	(-3.17)	(-1.93)
Number of Disasters (Sept-Dec)	-0.00211	-0.00718***	0.00715	-0.00235	0.00970*
	(-1.26)	(-3.52)	(1.81)	(-0.56)	(2.37)
Observations	201975	201975	201975	201975	201975

Note: The reported estimates are the marginal effects on the censored observations (Y|Y > 0). As fixed effects have been found to be inconsistent with non-linear tobit models, and no non-parametric solution has been devised, the individual controls are included as random effects. "Other" includes nonprofits in NTEE major group IN (International, Foreign Affairs), EN (Environment and Animals), PU (Public, Societal Benefit), RE (Religion Related), MU (Mutual/Membership Benefit), and Z (Unknown/Unclassified).

1.9 Robustness Checks

Table 18 shows that the main result of the paper is robust to alternative specifications and alternative samples. The first column replicates the main result from Table 8. The next several columns show alternative model specifications. The second column shows the result when the number of organizations is measured using the number of local organizations (rather than total organizations). The third column shows a regression with $log(Total\ Giving)_{zy}$ as the dependent variable. The fourth column shows two additional controls: first, a measure of the number of nonprofit establishments (from the QCEW data) in the zone, and second, a measure of the population density in the zone. The fifth column includes zone-specific time trends rather than zone fixed effects. The result is positive and so large as to be unbelievable. The coefficient is interpreted as a 1 percent increase in the number of organizations leading to a 3.3 percent increase in giving per employee. This can be explained by the short nature of the panel; these unit-specific time trends are likely to be highly variable and bias the results. The next three columns show alternative analysis samples. Column six excludes the DC region, which is unusual in terms of the number of federal employees and the hype surrounding the CFC.

The seventh column shows the results are robust to including only those campaigns that are believed to have very accurate measures of the number of employee participating (there is some concern that correlated measurement error in number of employees could bias results because of inclusion on both sides of the model). Finally, column eight shows that the results are robust to excluding 2013 data, since this was the year of the sequester.

Table 18. Robustness Results: Log(Per Capita Giving) and Log(Total Charities)

	(1) Preferred	(2) Local	(3) Unconstrained	(4) Extra Controls	(5) Time Trend	(6) No Capitol	(7) No Suspicious	(8) No 2013
log(Local+Natl Org Count)	0.00676		0.00676	0.424	3.383**	0.134	-0.381	0.435
	(0.390)		(0.390)	(0.443)	(1.119)	(1.011)	(0.393)	(0.443)
log(Number Employees Solicited)	-0.893***	-0.892***	0.107*	-0.943***	-0.270***	-0.893***	-0.949***	-0.940***
	(0.0542)	(0.0548)	(0.0542)	(0.0689)	(0.0647)	(0.0545)	(0.0666)	(0.0689)
Per Capita Personal Income	-0.00117	-0.00118	-0.00117	0.00261	0.00563	-0.00115	0.000638	0.00430
	(0.00676)	(0.00673)	(0.00676)	(0.00736)	(0.0101)	(0.00681)	(0.00890)	(0.00705)
Unemployment Rate	6.050	5.949	6.050	3.085	14.06	5.951	9.712	7.442
	(4.103)	(4.178)	(4.103)	(1.671)	(7.687)	(4.188)	(6.013)	(5.423)
Unemployment Rate × Unemployment	-23.74	-23.22	-23.74		-65.86	-23.63	-34.83	-21.47
	(20.22)	(20.71)	(20.22)		(34.68)	(20.95)	(28.01)	(26.73)
Proportion Female	0.266	0.235	0.266	-2.366	-2.341	-0.0131	-0.555	-2.389
	(2.654)	(2.685)	(2.654)	(2.496)	(1.783)	(2.789)	(3.492)	(2.506)
Proportion Permanent Status	-1.013	-1.006	-1.013	0.555	1.592	-0.912	-2.015	0.717
	(0.881)	(0.884)	(0.881)	(2.355)	(1.507)	(0.901)	(1.385)	(2.324)
Proportion Professional Category	0.145	0.147	0.145	-0.529	2.904	-0.0266	0.785	-0.762
	(2.560)	(2.560)	(2.560)	(3.302)	(2.420)	(2.576)	(5.576)	(3.285)
Proportion Administrative Category	2.662	2.642	2.662	2.121	2.780	2.203	1.829	2.075
	(1.821)	(1.818)	(1.821)	(2.271)	(1.618)	(1.874)	(3.131)	(2.265)
Average Salary	-0.00960	-0.00946	-0.00960	-0.0164	-0.0322*	-0.00950	-0.0429	-0.0163
	(0.00923)	(0.00916)	(0.00923)	(0.0101)	(0.0155)	(0.00958)	(0.0483)	(0.0104)
Average Length of Service	-0.0812	-0.0803	-0.0812	-0.0787	0.00872	-0.0860	-0.0150	-0.0813
	(0.0597)	(0.0587)	(0.0597)	(0.0673)	(0.0572)	(0.0627)	(0.0881)	(0.0671)
Average Age	0.110	0.110	0.110	0.130	0.00971	0.116	0.165	0.129
	(0.0873)	(0.0867)	(0.0873)	(0.110)	(0.0935)	(0.0899)	(0.129)	(0.110)
Proportion Postal Service	-0.0552	-0.0770	-0.0552	0.309	-0.496	0.223	2.477	0.581
	(1.271)	(1.283)	(1.271)	(1.371)	(0.811)	(1.324)	(1.927)	(1.407)
Proportion Uniformed Military	0.0987	0.0680	0.0987	0.818	-0.188	0.334	0.0371	0.884
	(1.135)	(1.175)	(1.135)	(1.570)	(0.579)	(1.209)	(1.656)	(1.569)
Disaster Allocation (Sept-Dec)	-0.00000744	-0.00000745	-0.00000744	-0.00000491	0.00000613	-0.00000656	-0.0000161	-0.00000654
	(0.00000588)	(0.00000582)	(0.00000588)	(0.00000783)	(0.0000124)	(0.00000588)	(0.00000833)	(0.00000776)
Number Disasters (Sep-Dec)	-0.00161	-0.00158	-0.00161	-0.00692	-0.00828	-0.00247	-0.00161	-0.00601
	(0.00496)	(0.00503)	(0.00496)	(0.00519)	(0.00787)	(0.00494)	(0.00632)	(0.00526)
log(Local Org Count)		0.00909						
		(0.0455)						
QCEWestablishments				0.00000208				
				(0.0000138)				
Population Density (Pop/SqMi)				-0.0000969				

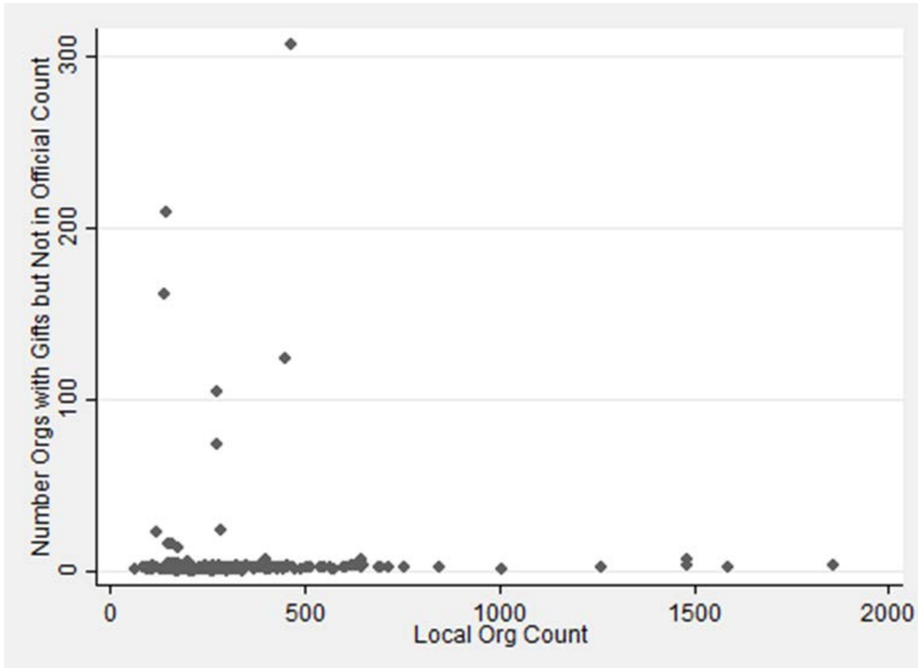
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				(0.0000575)				
Zone FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	744	744	744	584	744	728	361	584
Adjusted R^2	0.964	0.964	0.994	0.966	0.888	0.963	0.969	0.966

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors clustered at the local campaign zone level and adjusted for clusters. Campaign years 2010-2013 are included. Disaster allocation is in millions of 2011 dollars. Average salary and per capita personal income are in thousands of 2011 dollars.

1.9.1 Number of participating nonprofits

The individual data include cases where people make gifts to organizations not listed on the list of eligible organizations provided by the OPM. Since the list of eligible organizations is the source of the count of local organizations in the regression analyses, this indicates that the measurement of the count of local organizations may include some error. The statistical effect of mismeasured organization counts on the results differs depending on if the mismeasurement takes the form of an uncorrelated positive error (randomly missing organizations that are equally spaced among all geographic zones), positive error correlated with the organization count, or classic measurement error (random missing organizations and random extra organizations). When examining the scatter plot in Figure 9, it appears that there is a positive correlation with the organization count. If this is the case, then we can assume the bias is positive. This means that the coefficient value in the regression is overestimating the true relationship between the number of organizations and giving.

However, regressions of the number of potentially missing organizations on the organization count (Table 19) fail to find a positive correlation. In this case, we might conclude that the mismeasurement can be expressed as an uncorrelated positive error, which would have no effect on the coefficient of interest.



Note: Years 2010-2013 only. Only local geographic zones in the individual giving data.

Figure 9. Non-reported Organizations and Local Organization Count Scatter Plot

Table 19. Non-reported Organizations and Local Organization Count Relationship

	DV: Number Orgs with Gifts but Not in Official Count			
	(1) Basic	(2) Size Control	(3) Year FE	(4) Size Control+Year FE
Local Org Count	-0.00152	-0.00338	-0.00231	-0.00442
	(0.00158)	(0.00180)	(0.00107)	(0.00171)
Number Employees Solicited		0.0000234		0.0000266
		(0.0000199)		(0.0000182)
Year FE	No	No	Yes	Yes
Observations	205	205	205	205
Adjusted R^2	-0.005	-0.009	-0.006	-0.010

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Years 2010-2013 only. Only local geographic zones in the individual giving data. Clustered at the year level.

1.9.2 New organization giving

Another concern with the new charities is that they may be strictly inferior options. However, this does not seem to be the case, as there is positive giving to these organizations in each year observed. For those continually participating employees who are exposed to new organizations simply because those organizations choose to enter the campaign (truly "new" organizations, rather than organizations they are newly exposed to due to mergers), 3% of gifts were to new organizations post-2010.

1.9.3 Suggestive evidence of substitution patterns

The final analysis in this paper examines substitution from existing organizations to new organizations joining the CFC. This type of substitution is observable in the individual-level data for those employees making gifts through the Nexus online system. To create this data set, first I identify organizations that appear (or reappear) on donors' lists in 2011, 2012, or 2013. I then find the donor records associated with those gifts and identify a set of simple cases where substitution is easily identified. These include cases in which: 1) the donor only begins giving to one organization, and 2) the donor does not endogenously decide to increase or begin giving to another organization. This produces a data set of 972 substitutions to 416 new organizations by 675 individuals.

One common belief is that most donors substitute among organizations with similar missions. Therefore, competitive markets are often assumed to be organizations operating in the same subsector in the same geographic area. However, in the CFC, less than half of donors substitute within the same subsector. Table 20 shows patterns of substitution by 10 categories of NTEE-CC codes/charitable subsector. Using this subsector definition, about 42 percent of substitutions occur within subsector. If this analysis is repeated using 26 categories of NTEE-CC codes, which define nonprofit subsectors more narrowly, then only 27 percent of substitutions occur within subsector.

Table 20. Patterns of Substitution Between Existing and New CFC Organizations

	Sector of New Organization										
Sector Losing Org	AR	ED	EH	EN	HE	HU	IN	PU	RE	U	Total
AR - Arts, Culture, and Humanities	1	0	0	1	1	3	2	4	0	1	13
BH - Higher Education	0	0	0	0	0	1	0	0	1	0	2
ED - Education	1	7	0	0	3	6	1	6	1	4	29
EH - Hospitals	0	0	3	2	4	8	0	3	0	2	22
EN - Environment and Animals	2	2	1	86	16	14	1	7	0	19	148
HE - Health	2	3	6	24	74	59	5	26	6	12	217
HU - Human Services	3	5	4	25	33	142	10	36	11	22	291
IN - International, Foreign Affairs	1	2	0	3	7	16	6	14	1	3	53
PU - Public, Societal Benefit	7	5	0	11	13	35	2	29	4	8	114
RE - Religion Related	0	0	0	0	1	9	1	1	5	2	19
U - Subsector Unknown	0	0	1	9	11	23	2	6	6	6	64
Total	17	24	15	161	163	316	30	132	35	79	972

Note: Sample includes only simple substitutions (one new org chosen, no other new gifts made). No new organizations of type BH appear in this sample.

1.10 Discussion and Conclusions

Both of the functional forms examined here suggest that an increase in the number of nonprofits in the market does not lead to a significant increase in giving. There is no evidence that any relationship exists on the intensive margin; participation does not change with the number of nonprofits in a campaign. A positive relationship may exist between the number of nonprofits in a market and the gifts of participating individuals, although any effect is small when compared with the average gift over this time period.

One story reconciling the potentially disparate results for donors and non-donors is a story of donor attention. Donors might be better informed than non-donors about the list of charitable options. If employees are not in the habit of giving to the campaign, they might not examine changes in their choices from year to year. But employees in the habit of giving might review the list of options more closely and make more active decisions based on the new list of participating nonprofits. It is possible that the overall/per-capita giving correlations, which combine individuals on these two margins, are positive, but that the sample size is insufficient to detect this relationship. If such a story were to be true, it would be consistent with a model of donor decisionmaking where nonprofits produce heterogeneous public and private goods, where donors have heterogeneous preferences, and where increasing the number of nonprofits marginally increases the quality of the match between donors and nonprofits.

Even if one believes that a positive relationship between the number of nonprofits and giving exists, the magnitude of this effect means that entry has a negative effect on existing nonprofits. In other words, the giving market does not expand sufficiently to support the new nonprofit—the average entrant also "steals" donations from existing nonprofits. For example, consider a market like the Metropolitan Denver Area CFC, which has $3.05M gifts in 2011 and 2886 charity choices (including national, international, and local charities) available to 35,900 potential donors (6,200 of whom contributed).

Taking the most generous positive and significant point estimates from the earlier analysis ($0.07 increase in average gift) would indicate that a one-charity increase is correlated with decreases in per-nonprofit donations from $1055.56 to $1055.35. We can also consider the effect of adding 100 charities to the Denver CFC list (the typical increase in national options each year). In this scenario, per charity giving falls to $1035, which is a 2% decrease.

From the results of this study, it seems that both of the narratives discussed in the beginning are true. New nonprofits do increase giving among current donors (leading to support for the traditional microeconomic view of how variety changes consumption being confirmed in the case of the nonprofit sector). This confirms some of the claims of those with a positive view of nonprofit proliferation. However, perhaps because of attention issues, they do not increase the number of people giving, at least in the context studied. Furthermore, the new nonprofits don't increasing giving enough to avoid a “stealing” effect. Therefore, the average giving to each organization decreases, confirming the negative perceptions of nonprofit proliferation as well.

These results find that increasing the number of nonprofit choices does not significantly increase charitable giving and leads to “stealing” from existing nonprofits, at least in the context of the CFC. If this is true more broadly, what is the effect of nonprofit proliferation on the production of goods and services by the nonprofit sector? The answer depends on whether new organizations influence existing organizations to lower fixed costs or otherwise increase the productivity of the nonprofit sector. Under a case with sufficiently high fixed costs and limited productivity gains, then increasing the number of nonprofits may decrease the amount of public goods produced. One the other hand, if administrative costs are endogenous, as in Aldeshev and Verdier (2010), then new nonprofits may be more productive than older nonprofits or cause older nonprofits to be more productive. Thus, increasing the number of nonprofits could prompt nonprofits to increase the output for a given level of donations, increasing the likelihood that public goods increase when the number of nonprofits increases. Determining which of these scenarios is occurring as the number of nonprofits in the United States increases requires further study.

A few caveats are in order for this study. It is possible that workplace giving may be unusual in terms of social pressures (Carman 2004), and social pressure has been shown to increase giving, although it is likely to exert a psychological cost on potential donors (DellaVigna et al. 2010). Mental accounting also notes that giving may differ depending on the source of the income. Thus, giving from non-earned income, such as windfall income or perhaps even capital gains, may be different. If future work shows that there are differential motivations for giving in the workplace, this may limit the external validity of the results.

This study examines the relationship between the boom in nonprofit organizations and the charitable resources that those organizations are able to access. It provides evidence that new nonprofits do not significantly increase the charitable resource pool. Instead, a larger group of organizations cuts the “giving pie” into increasingly smaller slices. The results here also contribute to the literature on donor decisionmaking. The results suggest that heterogeneous preferences and the quality of match between donors and nonprofits are not significant factors in giving at the population level, although this may be because the majority of potential donors are not attending to opportunities new nonprofits provide to increase their match quality and their utility. However, more research is needed. One natural next question is whether the same behavior is observed in a non-workplace setting or in a setting where the decision to donate is made over time. In any case, identifying the effect of the nonprofit boom on charitable resources is an important avenue for future research. If government agencies, and other large funders and influencers, understand the costs and benefits of nonprofit fragmentation and competition, they can more effectively target funding and regulations to ensure that growth serves, rather than detracts from, social welfare.

2. Chapter 2: A Donor-based Concept of Nonprofit Competition

2.1 Overview

This paper proposes a new definition of nonprofit markets based on individual-level donor behavior and donor-nonprofit network ties. Empirically defining markets in the nonprofit sector has been difficult, because the well-established empirical industrial organization method of market definition uses price data, and it is therefore not applicable to nonprofit donations. Instead, nonprofit scholars rely on market definitions based on an organization's subsector and geographic location. However, these definitions fail to capture important facts about donor behavior. This paper defines nonprofits as competitors if they have overlapping donors. The definition is validated with data from the Combined Federal Campaign (CFC). The validation exercise shows that the new market definition predicts donor substitution among organizations 58% more accurately than the standard nonprofit market definition based on an organization's subsector and geographic location. The CFC data and this donor-based market definition are also used to examine an important nonprofit policy issue—the relationship between market concentration and nonprofit spending on overhead.

2.2 Introduction

Nonprofit organizations in the United States are often advised to distinguish their work from their competitors to increase the number and amount of donations they receive. Because donations are the most important source of revenue for nonprofit organizations, defining competitors accurately is important.[4] If a nonprofit's leaders are not able to correctly identify their organization's competitors, then they will not be able to devise effective competitive strategies. Nonprofit leaders typically have an easy time recognizing competitors with similar services. A local dog rescue organization may easily identify a local humane society as a competitor for donations. The leaders of the dog rescue organization may have a more difficult time deciding if other, less-similar organizations are competitors, including organizations such as a local wildlife rescue organization, a national dog rescue organization, a national animal rights advocacy organization, or a local park organization that maintains dog parks around the city. Finally, the organization's leaders may wonder if their fundraising is likely to be affected by focusing events in the news that spur a rise in disaster giving or political giving. The set of competitors arguably depends on the preferences and profile of the dog rescue's donors. If most of the donors identify primarily as dog-lovers, then national dog-related organizations are also important competitors. If most donors are those who adopted from the organization in the past and are interested in giving to organizations they use

[4] For 52 percent of nonprofits, donations make up more than 50 percent of the revenue. Other sources of revenue include government grants and contracts, investment income, and income earned from the sale of goods and services. Figures are based author's own calculations from National Center for Charitable Statistics Core Data files. The calculation captures only nonprofits that are required to file annually with the IRS. The percentage of revenue from donations is based on a six-year average (2007-2012). In addition, donations are the largest source of revenue for several sectors, including arts and culture, environment and animals, international, and other pubic charities (which include religious charities).

personally, the local dog park would be an important competitor, but other totally non-pet organizations such as local libraries or museums may also be competitors. Finally, if most donors give because they are opposed to euthanizing abandoned pets, then other animal activism organizations would be important competitors. The current models of nonprofit competition ignore donor characteristics and behavior, and instead focus on defining nonprofit competition based on classifications of the nonprofit's mission area.

In this paper, I propose a new method of defining nonprofit markets. The new market definition method is based on empirical analysis of individual-level donor decisions. Donor decisions shape a network of nonprofits, where connections between nonprofits are determined by the number of donors that they share. Nonprofits connected by shared donors form a competitive market. To evaluate the performance of the market definition and demonstrate its usefulness, I implement the empirical procedure using individual-level giving data from the Combined Federal Campaign (CFC), which is the workplace giving program of the federal government. I show that my market definition predicts future donor substitutions between nonprofits more accurately than standard market definitions. This more accurate definition lends credibility to research about the effects of competition on nonprofit behavior. Finally, I use the data from the CFC and this improved market definition procedure to examine the relationship between market concentration and nonprofit spending on overhead. I find that the new market definition generates different conclusions from the traditional definition about the relationship between market concentration and overhead in the nonprofit sector.

Nonprofit organizations compete in multiple ways. Some forms of nonprofit competition are the same as in the typical for-profit case, because some nonprofits provide goods and services to paying customers. For instance, nonprofit theatres compete to sell tickets, and universities compete to attract tuition-paying students. Other forms of nonprofit competition, however, are not experienced by a for-profit firm, at least in the same way. One of these is competition for donors, the focus of this paper. Theatres compete for donations that are not tied to ticket sales, and universities compete for dollars both to fund buildings and to fund scholarships that will be utilized by non-paying students. Donors can be thought of as either providers of capital or as “third-party payers” for these types of nonprofit goods and services. In practice, nonprofits engage in competition using various means, such as marketing the organization to current and prospective donors.

Empirically modeling competition among either for-profit firms or nonprofit organizations involves two implicit steps: defining the set of competitive organizations and measuring the intensity of competition among these organizations (Wong et al. 2005). This paper concentrates on defining the set of competitive organizations in the market. If the market is not correctly defined, then any measure of competition will not be accurate.[5] In the context of competition for donations, the relevant market is the set of nonprofit organizations that consumers perceive as substitutes. Consumers choose among these organizations when making a donation decision.

Complicating this market definition in the nonprofit context is the fact that the goods and services nonprofits produce are not homogeneous. If nonprofits produced just a few types of identical products, then an organization's competitors would be easy to identify. Instead, nonprofits produce heterogeneous goods and services differentiated along several dimensions. The programs offered by theatres, after-school programs, and community improvement organizations vary in multiple ways among organizations, making defining competitors difficult.

When confronting such heterogeneity among goods produced by for-profit companies, industrial organization economists typically use models of cross-price elasticity to define the relevant market.[6] They observe how consumers change their spending on one good in response to changes in the price of another good. A significant

[5] Economists have long sought to summarize the competitive intensity facing firms within a market in a single index. Competitive intensity is a concept regarding firm behavior, but this behavior is difficult to observe. Therefore, most indexes have instead measured market concentration, a measure of structure. While it is commonly recognized that such indexes can be no more than approximations of industry competitiveness on their own without other assumptions (Seaman et al. 2014), they are a useful starting point for discussion. The Herfindahl-Hirschman Index (HHI) is the most commonly used measure of competitive intensity. It measures the extent to which resources are concentrated among few, presumably oligopolistic, organizations or distributed among many, potentially competitive, organizations. It is calculated by taking the sum of the squared market shares for each firm in the market. Usually, values are measured using integers from 0 to 10,000.

[6] A positive cross-price elasticity indicates that two goods are substitutes, because consumers purchase more of good A when the price of good B goes up. A negative cross-price elasticity indicates that two goods are complements, because consumers purchase less of good A when the price of good B goes up (they also purchase less of good B).

spending change indicates that two firms are competitors. In the nonprofit sector, this technique can be used when organizations charge prices for their goods and services. If an enterprising theatre lowers its ticket prices and attracts many new audience members, then other theatres that lose audience members are considered competitors to the enterprising theatre.[7] Cross-price elasticity models cannot be used in the context of donations, however, because no set prices exist. Instead, nonprofit researchers use models that define the market based on a combination of subsector (such as health, education, etc. – the nonprofit equivalent of an industry) and geographic boundaries (typically metropolitan statistical areas or MSAs).

Using subsectors and MSA's to jointly define local subsector markets for donations is not ideal for two reasons. First, donation decisions do not fit neatly into the local subsector paradigm, and second, data quality at the local subsector level is poor. The first of these reasons is the most important. Defining the geographic and the subsector boundaries for donative markets is difficult. Geographic market definitions are complicated by the fact that, while some donors give a large portion of their gifts to charities within their local community, other donors give to organizations nationally or internationally. Defining subsectors that partition the nonprofit sector is complicated by

[7] It is theoretically possible that some theatres may be complements to the enterprising theatre, and may see their audience increase. This situation might occur if the enterprising theatre's low ticket price attracts audience members who had never been interested in theatre, and those audience members later attend more expensive shows at other theatres. I abstract away from this possibility for the sake of simplicity.

the fact that many nonprofit services do not fit neatly into one category. An example helps to illustrate why it is difficult to assign nonprofits to subsectors that reflect the diversity of donor interests. Consider a donor to an after-school program that provides arts apprenticeships to urban, low-income youth. Donors could have many reasons for giving to this nonprofit organization. Some donors may classify the organization as "arts and culture," while others may think of it in the category of "children and youth" or "jobs and employment."[8] Furthermore, while some donors give only to a closely related set of organizations, others give much more broadly, and the characteristics they prioritize may be difficult to observe. Other donors to the after-school program may be substituting among organizations in categories that may not match traditional subsector definitions, such as "community improvement organizations" or "high-status organizations" (if the organization is particularly well-networked).[9]

Neither cross-price elasticity models nor local subsector models reliably define market boundaries in the nonprofit sector. What is called for to advance research on nonprofit competition is an empirical method of defining nonprofit markets without using

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[8] A related issue is that donors to an organization are arguably more heterogeneous than consumers of that organization's goods and services. Goods and services arguably have more concrete attributes than the "product" that is purchased when one donates to an organization. By purchasing the nonprofit's product, consumers agree that the product's characteristics are worth the price charged. Since the consumers agree, they have something in common, and are arguably more similar than donors whose expenditures don't have concrete attributes or a fixed price.

[9] Defining the market based on field of interest model incorrectly assumes that donors mostly agree on the nature of the public good provided by the organization. Furthermore, it assumes that concern for production of the public good is the only motivation for donating to the organization, but donors might also compete with other "high status" or "politically connected" organizations for reasons that are less related to the public good than personal benefits.

price or traditional classification systems. The ideal market definition should reflect actual donor decisionmaking among organizations. For instance, if two organizations are defined as being in the same market, then marketing or fundraising actions that increase giving to one organization should decrease giving to the other organization in the market.[10]

In this paper, I introduce an empirical method of defining nonprofit markets based on revealed donor behavior. By observing donors who give to two or more organizations, I construct a network of organizations with links that indicate that the organizations share donors. According to this new definition, nonprofit organizations compete when they have overlapping donors.[11] The competition exists because when a donor chooses to give more to one of the nonprofits in her network, she may decide to give less to other organizations in her network, even if she does not have a fixed charitable giving budget.

One consequence of this market definition is that each organization has a unique market. To clarify, consider the markets of organizations A and B. Donors that give to organization A determine A’s market, which will include organization B if the two organizations share donors. A’s market will also include organizations C and D if they share donors with A. Now consider B’s market. Organization B’s market will also

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[10] If the giving to the second organization increases as well, then the two organizations would be considered complements.
[11] Section II discusses the degree of overlap that is necessary for two organizations to be considered substitutes and, therefore, competitors.

include organization A since the two share donors. However, Organization B's market may not include organizations C and D if those organizations do not share donors with organization B. Organization B's market may instead consist of A, E, and F. Organizations A and B have unique markets reflecting the fact that each organization faces unique competitive environments and pressures. Because A and B share some donors, their competitive environments (and therefore their markets) overlap, but A faces some competitors not shared by B, and vice versa. The competitive characteristics the two organizations face will not be identical, but they will be correlated.

The proposed method of empirically defining a nonprofit donor market has three consequences that are beneficial for research. First, because each organization has a unique market, I can calculate organization-specific, time-varying measures of market characteristics, such as market concentration. Organization-specific measures are intuitively appealing, since they reflect the fact that each organization faces a different competitive landscape. Second, organization-specific, time-varying market characteristics allow me to use organization fixed effects, which control for unobserved factors that do not vary over time. Finally, having data at the organization-year level rather than the MSA-year level increases the number of observations and therefore the power of the analysis.

To demonstrate the usefulness of this approach and to evaluate my market definition, I implement the procedure using individual-level giving data from the

Combined Federal Campaign (CFC). This context allows me to observe the list of soliciting nonprofits as well as annual, individual-level pledges by federal employees who give. For each donor, I observe both the nonprofits she selects and the amount she gives to each organization.

These data allow me to compare the performance of my new donor-based market definition to the standard subsector market definition. For each nonprofit, I construct the relevant market of competing organizations under the proposed donor-based definition and the standard subsector definition. Then, I construct a data set of actual gift substitutions after an exogenous exit of a CFC nonprofit. For each definition, I count the number of substitute organizations that are part of the exiting organization's competitive market. I find that the donor-based market definition predicts substitutions 58% more accurately than the standard definition. The test shows that the donor-based market definition predicts donor behavior and that the fundraising actions of one organization affect giving to other organizations in the market.

Using the CFC context, I am also able to examine an important nonprofit policy issue—the relationship between competition and nonprofit spending on overhead—and compare the results obtained from the subsector and donor-based market definitions. By comparing the two analyses, I demonstrate how market definition influences researchers' understanding of competition in the nonprofit sector. Understanding how nonprofits may change their operations in response to competition from other organizations is important for evaluating the effects of a variety of public policies. Nonprofits may respond by changing their spending on fundraising and related overhead expenses such as communications. Organization-level changes in overhead spending, when aggregated, can affect the amount of public goods, social services, and other programs provided by the sector, and are therefore an important consideration for policymakers.

The direction of the change in overhead spending is theoretically ambiguous. Increasing fundraising expenses allows an organization to reach more potential donors, but decreasing overhead expenses, and therefore increasing the proportion of funds going to program services, makes the organization more attractive to donors (Rose-Ackerman 1982, Okten and Weisbrod 2000). Existing research draws mixed conclusions about the relative size of these effects, with some empirical work finding that competition increases overhead spending and other work finding that nonprofits in more competitive environments spent less on fundraising individually, but more in the aggregate (Feigenbaum 1987, Thornton 2006).

Using the data from the CFC, I construct markets using both the traditional subsector market definition and the new donor-based market definition. I then measure competition intensity within these markets. Following previous literature, I measure competition intensity using the Herfindahl-Hirschman Index (HHI). The HHI is a measure of market concentration that specifies the extent to which a market's resources, in this case donations, are concentrated in a few organizations or, conversely, spread among many organizations. The HHI is often used to measure competitive intensity, which is difficult to observe.[12] Using the traditional subsector market definition, all nonprofits in the same subsector share a HHI. Using the new donor-based market definition, organizations have unique HHI measures that vary over time, because organizations each have unique markets. For each of the two analyses, I regress overhead rate on HHI, on total dollars given to each nonprofit, and on other relevant controls, including fixed effects.[13]

Using the traditional subsector market definition, I find that when a subsector's market concentration increases over time, there is no change in overhead rates. Using the donor-based market definition, I reach a different conclusion. I find that when an organization's market concentration increases over time, there is a (marginally) statistically significant increase in overhead rates.[14] More concentrated markets have less competition, so this result indicates that increases in competition are correlated with more efficient nonprofits. This result also suggests that competition may make nonprofits more efficiency-conscious and may play a role in decreasing rent seeking and "slack" among nonprofits. This application demonstrates that the new donor-based market definition

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[12] The logic of using concentration to measure competitive intensity arises from the observation that monopolies, in which resources are concentrated in one firm, are anti-competitive, while atomistic markets, in which resources are distributed among a large number of firms, are highly competitive.

[13] Notably, the organization-year-level HHI measure combined and the longitudinal CFC data allow me to include organization and year fixed effects when using the new market definition. I include subsector and year fixed effects when using the traditional market definition.

[14] Significant at the $p<0.1$ level only. Note this relationship is not causal, as a valid exogenous shock is not present in the data.

leads to a better understanding of how nonprofit organizations respond to competition.

This paper contributes to the methods available to nonprofit scholars by devising a new way to define nonprofit markets. With the right data, this new method can be applied to a wide variety of nonprofit contexts, allowing researchers to better understand how organizations in the nonprofit sector responds to competitive pressures. In particular, competitive pressures in the nonprofit sector can be influenced by a variety of policies, such as policies that promote social entrepreneurship, confer grant- and contract-based government funding, or alter the incentives for donating to nonprofits. This method of defining nonprofit markets can help to quantify nonprofits' behavioral responses to competition. Second-order behavioral responses by nonprofits to policy changes are important, and policymakers should account for these responses in their calculations of the social costs and benefits of new policies affecting the nonprofit sector.

The paper proceeds as follows: Section II provides the theoretical framework for understanding competition in the nonprofit sector. Section III reviews existing empirical approaches to defining markets to provide a context for the approach taken here. Section IV describes my proposed market definition procedure in detail. Section V explains the CFC and how the procedure is operationalized in the data. Section VI compares the new donor-based market definition to the traditional subsector market definition. It describes the overlap in the two measures and validates the new measure. Section VII describes the method of analysis for the application. It then compares the results obtained using the new donor-based and traditional subsector market definitions. Finally, section VIII concludes.

2.3 Overview of Nonprofit Competition

This section begins by establishing two important facts about competition and donations in the nonprofit context. These facts then form the basis for a model of donations to nonprofits in a competitive environment. Finally, I discuss the implications of this model for using individual-level donation records to define nonprofit markets.

2.3.1 Stylized facts about competition and donations to competing nonprofits

The first important fact is that nonprofits produce heterogeneous public goods and social services. Because nonprofit organizations produce heterogeneous goods, nonprofit leaders work to differentiate their organizations from others in similar subsectors along many dimensions. In the industrial organization literature, this is known as horizontal differentiation (one-dimensional differentiation is known as vertical, since the goods can be clearly ranked as better or worse in a single dimension). Although many organizations may seek to provide a similar public good, such as higher education, they differentiate themselves on the basis of methods of production, population served, or even intangible, brand-related aspects such as values espoused in marketing and communications (Brown and Slivinski 2006). Thus, two universities operating in the same state may develop programs and reputations focused on technology or liberal arts, or two nonprofits aimed at encouraging more low-income and minority students to pursue higher education may do so by offering scholarships or by offering assistance filling out the necessary paperwork to apply to schools and for scholarships. Donors and consumers are sensitive to these distinctions, and may give more to one organization over another because they agree with the organization's approach, feel more empathetic toward the population it serves, or are more inspired by its marketing pieces.

The second important fact is that many donors give to several charitable organizations over the course of a year, and often these organizations are in multiple subsectors and locations. According to a recent survey of active donors by Cygnus Applied Research, respondents age 35 to 64 gave, on average, to 9 organizations in 2015, and donors over age 65 gave, on average, to 14 organizations (Burk 2016). Donors making larger gifts from accumulated assets also give to multiple organizations. According to a Fidelity Charitable (2016) report, 85% of individuals with Fidelity Charitable Donor Advised Funds gave to 6 or more charities in 2015. Donors making multiple gifts tend to give to more than one nonprofit subsector. According to the 2005 Center on Philanthropy Panel Study (COPPS), most donor households give to more than one type of nonprofit organization.[15] The number of organization types supported tends to increase as a donor household's income increases. Donor households with income over

[15] COPPS asks households if they made gifts of $25 dollars or more in the previous year. If so, the households are asked separately about giving to 11 different types of nonprofit organizations. These organization types do not align perfectly with the NTEE major group codes I use in this present study. Therefore, I use the "nonprofit organization type" terminology of COPPS to distinguish this classification scheme from the more common scheme I am using.

$100,000 gave, on average, to 3.5 types of nonprofit organizations, while donor households with income less than $50,000 gave, on average, to 2.3 types of nonprofit organizations. Finally, donors give to charities based outside of the donors' local area. According to the Fidelity Charitable study, only half of donors' grant dollars went to their home states (2016).

2.3.2 Modeling competition and donor decisionmaking

Competition among heterogeneous, horizontally differentiated organizations has been modeled using "locational" representations. Locational representations were introduced by Hotelling, in the form of a one-dimensional "linear city" model (1929). Later extensions took on multiple dimensions.[16] In the multi-dimensional model, organizations differ on (finitely) many characteristics, and these characteristics are represented in an n-dimensional unit space known as the "product space." The organizations are then located within this space by quantifying each differentiated characteristic. Figure 10 shows how a group of theatres differentiated on two characteristics—type of stories produced and target audience—would be represented using a two-dimensional locational model. In the figure, one can see that Theatre A produces more new works than Theatre B. Theatre B produces more child-friendly productions than Theatre A. In addition to representing organizations, this model also

[16] For a review of these multi-dimensional models see Lancaster (1990).

represents customers on the product space by using their preferred sets of characteristics as their "ideal points" or locations.

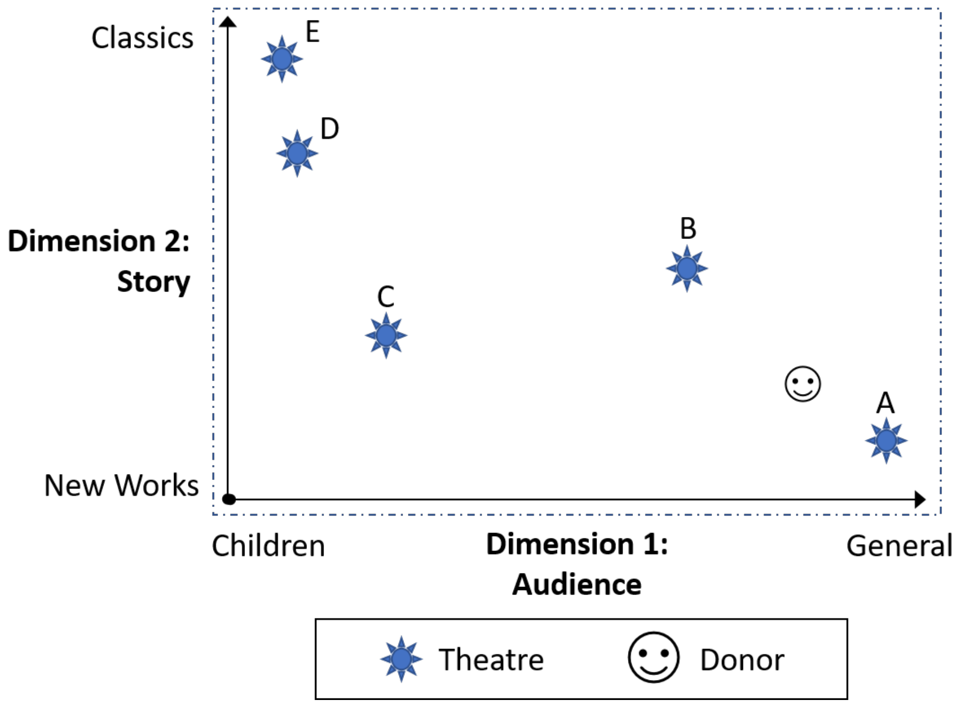

Figure 10: Simple Representation of Horizontal Differentiation in the Nonprofit Sector

Using a locational model, donor decisionmaking is straightforward as long as the donor chooses only one organization. In this case, the donor gives to her most preferred organization, which is also the closest organization to her on the diagram. In Figure 10, the donor shown is closest to Theatre A, and so would choose to give to Theatre A. The amount she gives depends on the marginal benefit she gets from giving compared to the marginal benefit from spending that money on all other (non-charitable) consumption.[17]

If a donor has an ideal point but also values variety, then he or she may give to multiple organizations. Preference for variety is often explained by diminishing returns from purchasing additional quantities of a most preferred good. After purchasing some initial amount of the most preferred good, a consumer will begin to purchase a second good. Donors may value variety because they experience diminishing marginal utility from additional dollars donated to a cause, or for other reasons. For instance, donors may believe that multiple organizations working on a problem encourages innovation, or they may get some social benefit from being known as a donor to more than one organization. As donors' appreciation for variety increases, more donors will give to multiple organizations. In Figure 10, if a donor values variety, she would give first to Theatre A, and then to Theatre B, which is her next-most-preferred organization.

2.3.3 Implications of the model

Using the models discussed here, a researcher can learn about the distribution of charities and donors in the product space based on the donors' giving. At the most basic level, when a donor gives to one nonprofit organization, this tells the researcher what her most preferred nonprofit organization is. The gift also reveals that the donor and

[17] The donor equates marginal utility from both donations and other consumption. This formulation of donor decisionmaking abstracts away from strategic considerations regarding the giving of other donors and considerations of the motivation for giving, including utility derived from consuming a public good and utility derived from the act of giving, which the literature terms "warm glow."

nonprofit organization are located near each other within the product space.

When a donor makes multiple gifts, this tells the researcher even more about the distribution of nonprofit organizations within the product space. Donors making multiple gifts are trading off between organizations that are close substitutes. This tradeoff process is only possible if the organizations are both located near the donor in the product space, and it follows that those organizations are located near each other as well. Organizations near the same donors will then be competing for these donors' contributions.[18]

Before moving on, it is important to note that any particular individual may consider organizations that the individual does not choose to be substitutes for those they do choose. However, given a population of enough individuals with slightly varying preferences, the observed choices at the population level will include some donors who give to both organizations. While observing one individual's choices may not provide a full understanding of the set of competitive organizations, observing a full population of individual donors' choices will uncover the full set of competitive organizations. Therefore, a large number of donors must be observed to ensure that the full set of competitors is captured. If a researcher observes only a small number of donors to a particular nonprofit, they cannot reasonable assess whether the competitors observed are

[18] Here, I take the form of competition employed by organization to be exogenous. Competition could involve advertising, providing a different mix of public goods and social services, cutting overhead rates, or some other actions.

the full competitive set.[19]

2.4 Empirical Measures of Markets in the Literature

In the nonprofit literature, the relevant market for nonprofit competition is usually defined as the set of nonprofit organizations operating in the same subsector in a particular geographic region. This literature is summarized in Table 21, which describes ten papers that were selected because they relate to nonprofit competition or entry and measure the competitive nonprofit market.

As shown in the table, nine of the ten papers use MSA as the geographic scope of the nonprofit market. In addition, nine of the ten papers use the National Taxonomy of Exempt Entities (NTEE) codes or a related mission designation to define the product scope of the nonprofit market. For instance, Seaman et al. (2014) define the market as organizations in the same NTEE category in the same MSA. Intensity of competition or market power is typically operationalized using the HHI (Thornton 2006, Castaneda et al. 2007, Seaman et al. 2014, Twu 2007, Bose 2015) or the number of organizations per capita (Twombly 2003, Saxton and Benson 2005, Barman 2008, Twu 2007)[20], with some papers using multiple measures.

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[19] In the present paper, I observe over 65,000 donors and exclude nonprofits which receive fewer than 10 gifts from most analyses.
[20] Some papers use other related nonprofit count variables.

Table 21: Market Definitions in Nonprofit Literature

Paper	Product Boundary	Geographic Boundary	Intensity Measure	Dependent Variable	Findings related to competition
Feigenbaum 1987	"Medical Research Funding" organizations	7 metropolitan markets	4-firm Concentration Ratio	Spending ratios (admin, fundraising, research)	Concentration inversely related to research spending and fundraising; positively related to administrative spending
Twombly 2003	Human service organizations	53 MSAs	Number of organizations/ population in poverty; 5-org concentration ratio using gross income	Probability of exit; rate of entry	Low nonprofit density has a positive relationship with entry; nonprofit density is unrelated to exit
Saxton and Benson 2005	501(c)(3) organizations	284 counties	Number of organizations	Number of new organizations	Organizational foundings are positively related to prior organizational density
Thornton 2006	16 "Local" NTEE Subsectors	MSAs	HHI based on total revenues, also tested number of orgs	Spending on fundraising (org-level and market-level)	When donor markets become more competitive, nonprofits significantly decrease their fundraising expenditures and returns to fundraising decrease. Total fundraising expenditures increase when competition increases due to new firm entry.
Castaneda et al. 2007	16 "Local" NTEE subsectors	MSAs	HHI, CR4, FSI (population to support a new firm)	Expenditure shares	Competition reduces admin spending, increases fundraising spending
Barman 2008	Workplace charity/federated fundraiser organizations	123 MSAs	Number of nonprofits per capita	Presence of United Way rivals ("Alternative Funds")	United Way rivals are more likely when a city has a greater number of nonprofit organizations per capita

Harrison and Thornton 2014	15 “Local” NTEE Subsectors	CBSAs–MSAs	n/a	Number of organizations	Based on a normalized unit of demand for nonprofits, there is lower nonprofit density per demand unit in 2005 than in 1995
Seaman et al. 2014	NTEE major groups (25 categories)	20 largest MSAs	HHI and Gini coefficients	n/a	Subsectors and metropolitan areas vary in their levels of concentration and nonprofit expenditure inequality
Twu 2007 (unpublished)	Symphony Orchestras	MSAs	Various (organizations per capita, HHI included)	Fundraising efficiency (4 measures)	Concentration associated with lower net contributions but higher fundraising expenses ratios
Bose 2015 (unpublished)	16 “Local” NTEE Subsectors	MSAs	HHI	Public support donations	Increasing competition decreases average donations, has a positive effect on aggregate market donations

Notes: A literature search was conducted to identify empirical academic articles on the topic of nonprofit competition in the United States. The search process was conducted in the winter of 2016. The search spanned academic databases and the references of found articles. Only papers that included an empirical definition of the nonprofit market are shown here. Papers examining nonprofit entry (founding) and exit while controlling for level of competition between existing organizations are included here. Additional papers investigate the determinants of nonprofit density without controlling for competition explicitly, and so are not part of this table. These papers include: Corbin (1999), Grønbjerg and Paarlberg (2001), Matsunaga and Yamauchi (2004), Kim (2013), and Lecy and VanSlyke (2013). Within these papers, nonprofit density measurements typically use MSA or county as the geographic scope. Density is measured using number of organizations or number of organizations per capita.

In search of a method of defining nonprofits' competitive markets that better reflects the observed behavior of donors, I review empirical measures of markets in other literatures.[21] The industrial organization literature has developed multiple ways of defining competitive markets. Some of these measures are applied primarily to for-profit competition, and other measures are applied primarily to mixed-industry hospital market competition. Each of the measures from the industrial organization literature faces substantial hurdles to application in the nonprofit context.

2.4.1 Empirical industrial organization literature: For-profit industries

In the industrial organization literature, a major focus has been on defining the market for the purpose of evaluating antitrust claims. In antitrust claims, it is important to evaluate if two firms are operating in the same market. Market definition in antitrust claims is typically done using tests of cross-price elasticity and tests of substitution as a result of price increases, the most well-known of which is the SSNIP test (U.S. Department of Justice and the Federal Trade Commission 2010).[22] These tests evaluate whether a change in the price of one firm's goods shifts the demand curve for the other firm's goods to establish if these two firms are competitors.

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[21] Much of the theoretical and empirical work focuses not on competition for donations but instead on competition for the sales of goods and services. The focus on sales-related competition exists in the hospital context, but also can be observed in other industries where researchers have been interested in the mixture of nonprofit and for-profit organizational forms (see Schlesinger and Gray (2006) or Brown and Slivinski (2006) for a review of this literature).

[22] The merger guidelines state "Specifically, the [SSNIP] test requires that a hypothetical profit-maximizing firm, not subject to price regulation, that was the only present and future seller of those products ("hypothetical monopolist") likely would impose at least a small but significant and non-transitory increase in price ("SSNIP") on at least one product in the market, including at least one product sold by one of the merging firms." (p. 9)

Defining substitute products based on cross-price elasticity is problematic in the nonprofit context because there is nothing analogous to price. Many researchers create an analogy between the concept of price and the nonprofit's overhead rate (Meer 2014, Bowman 2006, Okten and Weisbrod 2000, Weisbrod and Dominguez 1986) . They note that, with a higher overhead rate, a donor must increase her gift if she wishes to purchase a specific amount of charitable goods and services. Even if the analogy between overhead rates and price is correct, it is not clear that donors respond to changes in overhead rates the same way that consumers respond to changes in product prices for two reasons. First, it is unclear whether donors are well informed about charitable overhead rates. Second, one component of overhead rates is fundraising expenses. Fundraising expenses have been shown to encourage donations (Frumkin and Kim 2001). It is difficult to separately identify the effects of the price-like overhead rate and the spending on fundraising. Empirical research has shown these donors' responsiveness to changes in overhead rates is relatively small when compared to other factors, even in cases where the information is clearly available (Bowman 2006, Frumkin and Kim 2001).

2.4.2 Empirical industrial organization literature: Hospitals

Not all industries produce the data necessary to carry out cross-price elasticity tests effectively, however. One important industry where price data are rarely used to define competitive markets is the hospital industry.[23] In the hospital industry, alternative market definitions have been used. Elzinga and Hogarty (1973) define a market's geographic boundary by product flows in and out of the area. Specifically, the Elzinga-Hogarty test defines the market as the smallest geographic area where no more than 10% (or 20% or 25%) of the goods and products consumed within the area are produced externally and, conversely, no more than 10% of products produced in the area are exported. Inspired by the Elzinga-Hogarty test, hospital researchers have also begun to use patient flows to define a market's geographic boundary. In the hospital literature, market geography is typically defined as a set of zip codes that send a non-trivial number of patients to the hospital and collectively account for a large percentage of hospital discharges.

In an influential paper on hospital competition, Kessler and McClellan (2000) expanded on the idea of using patient flows to empirically define a hospital market. They first estimate a patient-level hospital choice model and then empirically define the hospital's geographic market from the predicted patient flows. Unfortunately, applying a model of this type to the nonprofit sector by using donors rather than patients, is infeasible. Three problems arise that make a donor flow model impossible in most

[23] Using prices in the hospital context is atypical because consumers often do not have information on prices before selecting hospital care. Prices charged to consumers are also distorted by insurance. The prices paid by insurance providers are not the prices charged to the users of the hospital care. Notably the hospital industry includes both for-profit and nonprofit hospitals.

contexts (including this one).

First, the data required for a donor flow model are difficult to obtain. Individual giving data for the nonprofit of interest and all potential competitors would be needed. Individual giving data are available in the context of the CFC, but that is unusual.

Second, the number of nonprofit alternatives is typically much larger than in the hospital case. The large number of alternatives increases computational difficulty (or data required) for the donor choice model. One technique used in the industrial organization literature reduces the estimation difficulty by describing each choice by a set of attributes (Fader and Hardie 1996). To achieve this, nearly all attributes must be objective and observable. While objective attributes are easily available in industries such as the packaged grocery industry, where one would observe size, brand, and calories, nonprofits can be more difficult to describe in an objective manner and standard datasets may not contain the full range of objective attributes. Furthermore, because the number of options in the nonprofit data set is so large, even this technique will computationally difficult. To overcome this, the researcher may also need to sample the alternatives available to each donor, rather than estimating the model using the full set of alternatives. This additional step further increases the technical difficulty of estimation, and its application has been limited within the industrial organization literature (Keene and Wasi 2012).

Third, donors often give to several organizations in a short period of time. Assuming that these donation decisions are unrelated to one another may not reflect reality. In contrast, the hospital literature typically uses heart attack data or similar rare occurrences. In this data, one patient is typically admitted to one hospital for their heart attack. The typical assumption in the hospital setting is that each observed choice of hospital by a consumer is unrelated, which is reasonable in that context. Because nonprofit donors give to multiple organizations and the donors' decisions may be related, modeling the donations in a simple multinomial logit choice model would be incorrect.

More complex choice models are rarely used in the literature and are therefore underdeveloped. Most models from empirical industrial organization treat joint purchases as a challenge to be overcome, as it makes modeling the choice more difficult. However, it is possible that, if the choice set is known, simultaneous or joint purchases can be used to understand competition. Grover and Srinivasan (1987) use multiple purchases in a short period of time to estimate the joint probability of the same consumer choosing two different brands or items within a product category. These probabilities are then used to segment the consumers and define the market structure based on the level of predicted switching for the firm's market position.

2.4.3 Network science literature

Another literature concerned with defining competitive markets is network science. The network science literature arises out of the sociology tradition, and early sociological work on competition goes back to Granovetter (1985). This literature attempts to uncover the "structure of social relations" underlying competition using observation and self-reporting by organizations. Management reports of competitors typically define the competitive market in this literature. For instance, Braha et al. (2011) uses Hoover's research database, which is largely based on firms' own filings with the government, to form competitor lists. The resulting network shows a network of competition characterized by several factors, including geographic distance and firm size, rather than industry codes alone. In fact, only 46% of competitive network ties specified by firms were between organizations in the same industry (five-digit NAICS code).

Network science literature has been applied to the nonprofit sector, although literature specifically looking at funding-related networks (as opposed to service delivery networks) is sparse. Some of this literature has examined relationships among organizations based on shared board members (Moore et al. 2002, Faulk et al. 2016a). A recent paper by Faulk et al. examined shared board ties among nonprofits and foundations and found that more connected nonprofits were more successful in obtaining grants (2016a). Another recent paper by Faulk et al. examines networks formed by nonprofits that share foundation grants. This work concluded that organizations with more central positions in the network in early years received more grants in later years (2016b). To my knowledge, no researchers have published work examining networks of relationships among nonprofits based on shared individual donors.

2.4.4 This paper

The empirical strategy used here combines aspects of the economics, networks, and nonprofit approaches. Like in the network literature, I interpret the competitive landscape using a network. However, I do not follow the network literature in employing self-reports to construct the network. Instead, I follow the economics literature in using observed consumer (in this case, donor) choices to understand the competitive set. However, rather than estimating a multinomial logit choice model, I employ a simpler approach. I take advantage of the fact that donors jointly choose multiple nonprofits as a first step of constructing network ties between organizations.[24] Like the nonprofit literature, I use geographic location to constrain the donor choice set.

2.5 Proposed Market Definition Procedure

Empirically modeling competition, including nonprofit competition, involves two implicit steps: defining the competitive market revealed by donor overlap and calculating intensity of competition. This section will describe the first of these steps, the process for defining the competitive market.

I define two organizations, *i* and *j*, as competitors if at least some donors are likely to substitute donations to *i* for *j*. I use bundled donations, which are two or more donations that occur at the same time, as evidence that the organizations are near each other in the product space and close substitutes for the donor. The "competitive market for organization *i*" is organization *i* itself plus all the *j* organizations that share at least

[24] I do not currently approach this as a stochastic problem, but a probabilistic model may be useful in future extensions.

one donor. These relationships can be represented in a network model, which provides a visual representation of the product space described in Section II.

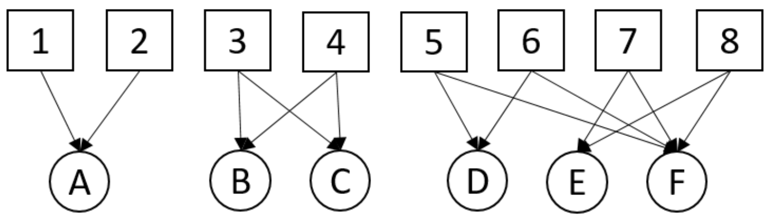
Figure 11 provides a simple illustration of the market definition procedure. The first panel provides a simple example of individual-level giving by eight hypothetical donors. These eight donors give to six organizations, labeled A-F. Some donors give to only one nonprofit organization, while others split their giving with pledges to multiple organizations. The second panel shows how these gifts can be represented in a two-mode (or bipartite) network. Donors are represented by boxes, and organizations are represented by circles. From this two-mode network, one can already observe that Organization A is not connected to other organizations, and is in its own market. One can also observe that organizations B and C are connected and form a market. Finally, one can observe that organizations D, E, and F are connected in a more complex manner. The third panel shows the inferred nonprofit network. In this network, nonprofits are represented by circular nodes. Ties between the organizations indicate that the nonprofits share at least one donor. This structure visually represents the competitive market defined by donor behavior. In the third panel, one can see that organization A has no connections (no common donors), while organization B and C are connected because they share donors. Organization F is connected to both D and E. However, because organizations D and E do not share donors with each other (each shares only with F), they are not connected. The fourth panel specifies the donor-based markets for each organization. The market for each organization consists of the organization and the organizations with which is shares donors. These are the organizations it is linked to in the network diagram, which are known as network neighbors.

It is important to note that the markets for organizations D, E, and F are distinct. Organization F shares donors with both organizations D and E, and so its market includes all three organizations. However, organization D does not share donors or a network tie with organization E. Therefore, its network includes only organizations D and F. Likewise, organization E shares donors only with F, and its market contains only these two organizations, not D. The three organizations have overlapping, but unique markets. As such, any market characteristics for these organizations will be different.

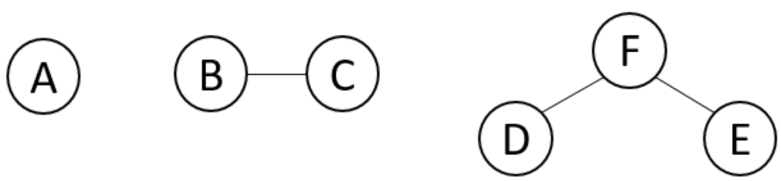
Panel A: Sample Gift Records

Donor	Org. A	Org. B	Org. C	Org. D	Org. E	Org. F
1	$40					
2	$40					
3		$20	$20			
4		$20	$20			
5				$20		$20
6				$20		$20
7					$20	$20
8					$20	$20
Total	$80	$40	$40	$40	$40	$80

Panel B: Two-mode (Bipartite) Network



Panel C: Inferred Nonprofit Network



Panel D: Markets

	Org. A	Org. B	Org. C	Org. D	Org. E	Org. F
Orgs. In Market	A	B, C	B, C	D, F	E, F	D, E, F

Figure 11: Network Modeling of the Competitive Marketplace

In a formal network model, organizations and relationships between competitive organizations can be represented by the set $G = \{V, E\}$. The organizations $V = \{v_1, v_2, \dots, v_N\}$ are represented as nodes. The relationships between competitive organizations, defined by donors' pledges to multiple organizations, are represented by an edge or tie between the nodes, $E = \{e_{ij}\}$.[25] Organizations v_i and v_j sharing n donors have $e_{ij} = n$. If no donors are shared $e_{ij} = 0$. Therefore the market for organization *i* could be described as its network neighbors, or the set of all organizations such that $e_{ij} > 0$. Equation 1 expresses this formally.

$$Market_i = \{v_i, v_j : e_{ij} > 0\} \qquad (1)$$

The definition in Equation 1 gives the market for organization *i* as its immediate neighbors in the network, or the organizations with which organization *i* shares donors. These are known as first-degree neighbors. The network model also allows for an expanded market definition that includes organizations that indirectly compete for donors. In network parlance, these organizations would be known as second-degree neighbors. Second-degree neighbors are organizations that share a first-degree neighbor—their donors are both interested in a common third organization. For some analyses, I test a second market definition based on second-degree neighbors.

[25] In network parlance, this is a one-mode representation of a two-mode, or bipartite network.

2.6 Context of the Combined Federal Campaign

I implement the proposed framework in the context of the Combined Federal Campaign (CFC), which is the workplace giving program of the federal government. This unusual data set allows me to observe the list of soliciting nonprofits as well as individual-level pledges by federal donors (nonprofits selected and amount donated to each).

2.6.1 Overview of the Combined Federal Campaign

The Combined Federal Campaign, or CFC, encourages and facilitates workplace giving by employees of the federal government. These employees are located in federal workplaces around the United States, and therefore the CFC is divided into local administrative zones. Employees within each administrative zone are provided with a list of eligible nonprofit organizations. Eligible organizations include local nonprofit organizations (those with services in fewer than 15 states), national nonprofit organizations (those with services in more than 15 states), and international nonprofits (those with services in at least one country other than the United States). To be deemed eligible, organizations must be a registered 501(c)3 nonprofit organization, must complete a simple application providing information about governance, program operations, and auditing practices, and provide a copy of the previous year's IRS Form 990.

Employees make pledges through the CFC at the end of each calendar year (generally between September and December).[26] Each employee receives a booklet of eligible organizations for his local administrative zone. In many campaigns (including all those in my data), the employee may also access this list online. The employee then chooses the organizations to which he wants to donate and makes either a one-time gift by cash or credit card or a recurring gift deducted from his pay. He can submit his choices either with a paper pledge form or through an online system.[27]

2.6.1 Data

I observe individual-level giving to the CFC between 2008 and 2013. For each year, I observe pledges made through one of the online giving and gift tracking systems serving the CFC. The system was in use by 62 local administrative zones by 2013. The pledges include information on which charities an individual selects and how much he or she gives to each nonprofit organization. I also observe the individual's zone. The data set includes approximately 18,650 public charities, 655,000 pledges, and 1.3 million gifts over the six-year period.

Table 22 shows how the coverage of the Nexus data grows over the course of the panel. The first three rows show that the number of local administrative zones, number of pledges, and number of gifts grows each year as the coverage of the Nexus system

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[26] Gifts in this context are called pledges because employees generally do not give one large donation; instead, most commit to an amount taken from each paycheck over the course of the year. As it is a commitment, rather than an immediate gift, it is known as a pledge.
[27] A few systems are available; in my data, most individuals use the Nexus system.

expands. Coverage expansion also leads to larger pledge totals in the sample each year, which are shown in row four, even though pledges to the CFC overall are falling over this time period. Rows five and six show that the average pledge and average gift decrease and then increase during this time period.

Row seven shows that the average donor chose about two nonprofits during this time period. Row eight shows the number of organizations selected by at least one donor who appears in the individual data. The number of organizations included in this data grows substantially over time.

Table 22. Summary Statistics for Individual Gifts and Pledges to the Combined Federal Campaign

	2008	2009	2010	2011	2012	2013
Number of Campaign Zones	17	25	37	47	59	62
Number of Pledges	11,197	50,955	97,643	117,756	154,292	222,897
Number of Gifts	23,418	96,244	176,133	220,601	291,020	476,752
Total Pledges (2011 dollars)	4,255,303	17,453,175	29,815,274	39,450,405	51,389,802	98,208,369
Mean Pledge (2011 dollars)	380.04	342.50	305.35	335.02	333.07	440.60
Mean Gift (2011 dollars)	181.71	181.34	169.28	178.83	176.59	205.99
Mean Gifts per Pledge	2.1	1.9	1.8	1.9	1.9	2.1
Number of Selected Nonprofits	3,618	6,302	8,542	10,514	13,832	16,362

Note: A pledge is one individual's donations across all selected organizations. A gift is one individual's donation to a single nonprofit organization. A pledge can include several gifts. This table includes only those individuals, pledges, and campaigns in the estimation sample.

2.7 Nonprofit Market Analysis

The present section begins by presenting two facts from the CFC data. Each of these facts supports the idea that the subsector definition of the competitive market is not the most useful definition to use in the nonprofit context. I then compare the new donor-based market definition to the traditional subsector market definition. Finally, I present evidence that the new donor-based market predicts a donor's behavior after an organization she has donated to in the past becomes unavailable for future gifts. Specifically, I show that the donor-based nonprofit market definition predicts the donor's new selection 58% better than the traditional subsector definition.

2.7.1 Stylized facts in the CFC data

Individuals who donate through the CFC behave much like donors in other contexts. First, over half of CFC donors give to multiple organizations. Individuals making more than one donation split their gifts among subsectors 82% of the time. Among these donors, 33% give to 2 subsectors, 25% give to 3 subsectors, and 24% give to 4 or more subsectors. A more granular form of these statistics is shown in Table 23. The columns show the number of donations made, X, and the rows show the number of subsectors selected to receive those donations, Y. The cells give the probability of an individual donor's pledge to X organizations being split among Y subsectors.

Furthermore, when new nonprofits enter the market, donors switch their donations from existing organizations to these new organizations. However, many of these switches do not happen within subsectors. In Table 24, I find all cases where donors made a specific kind of unambiguous switch after the entry of a new organization. These are cases where a donor stopped giving to exactly one organization and started giving to a new organization. These switches are relatively clear examples of direct substitution. Table 24 shows the number of times donors substituted between specific existing organizations (the rows) and new organizations (the columns), grouped by 12 NTEE[28] subsectors. It demonstrates that, in 58% of cases, the substitution was not occurring within subsector.

[28] In the United States, the National Taxonomy of Exempt Entities (NTEE) divides nonprofits into 26 service types. These are collapsed into major groups of nonprofit activities: arts, culture, and humanities (A), education (B), environment and animals (C, D), health, (E, F, G, H), human services, (I, J, K, L, M, N, O, P), international, foreign affairs (Q), public, societal benefit (R, S, T, U, V, W), religion related (X), mutual/membership benefit (Y), and unknown (Z). Hospitals and institutions of higher education are analyzed separately from health and education institutions to form a total of 12 groups.

Table 23. Donors Bundle Gifts from Multiple Nonprofit Subsectors

	Number of Gifts in Year										
Number of Sectors	1	2	3	4	5	6	7	8	9	10+	Total
1	47.26	8.467	1.968	0.732	0.348	0.077	0.030	0.013	0.004	0.013	58.911
2	-	12.281	5.972	2.896	1.655	0.464	0.145	0.056	0.027	0.053	23.550
3	-	-	3.405	3.208	2.755	0.941	0.398	0.202	0.089	0.198	11.197
4	-	-	-	0.927	1.495	0.791	0.406	0.251	0.119	0.409	4.397
5	-	-	-	-	0.244	0.264	0.176	0.144	0.100	0.428	1.355
6	-	-	-	-	-	0.028	0.031	0.041	0.040	0.277	0.417
7	-	-	-	-	-	-	0.001	0.005	0.003	0.110	0.119
8	-	-	-	-	-	-	-	0.001	0.000	0.043	0.044
9	-	-	-	-	-	-	-	-	0.000	0.009	0.009
Total	47.26	20.748	11.345	7.762	6.497	2.565	1.187	0.712	0.382	1.540	100.000

Note: Cells represent the percentage of donors who give X gifts to organizations from Y subsectors, where X is the column value and Y is the row value. The maximum number of subsectors a donor making 2 gifts can select is two, which means rows 3 to 9 in column 2 will always equal zero. Number of gifts for year was topcoded at 10. Subsectors are the 12 major NTEE groups (10 standard major groups plus Hospitals and Higher Education).

Table 24. Substitution Patterns Between Existing and New Organizations - Subsector of Substitution

	Sector of New Organization										
Sector Losing Org	AR	ED	EH	EN	HE	HU	IN	PU	RE	U	Total
AR - Arts, Culture, and Humanities	1	0	0	1	1	3	2	4	0	1	13
BH - Higher Education	0	0	0	0	0	1	0	0	1	0	2
ED - Education	1	7	0	0	3	6	1	6	1	4	29
EH - Hospitals	0	0	3	2	4	8	0	3	0	2	22
EN - Environment and Animals	2	2	1	86	16	14	1	7	0	19	148
HE - Health	2	3	6	24	74	59	5	26	6	12	217
HU - Human Services	3	5	4	25	33	142	10	36	11	22	291
IN - International, Foreign Affairs	1	2	0	3	7	16	6	14	1	3	53
PU - Public, Societal Benefit	7	5	0	11	13	35	2	29	4	8	114
RE - Religion Related	0	0	0	0	1	9	1	1	5	2	19
U - Subsector Unknown	0	0	1	9	11	23	2	6	6	6	64
Total	17	24	15	161	163	316	30	132	35	79	972

Note: Cells are counts of donors who substitute a gift in subsector Y for a gift to a new organization in subsector X, where Y are rows and X are columns. Sample includes only simple substitutions (one new org chosen, no other new gifts made). Subsectors are the 12 major NTEE groups (10 standard major groups plus Hospitals and Higher Education). No new organizations of type BH appear in this sample.

2.7.2 Markets in the CFC data

The donor-based market procedure was applied to the CFC data, and the market for each organization that received donations from the individual giving dataset between 2008 and 2013 was identified. Information about these markets is summarized in Table 25. On average, the donor-based markets include 11 organizations, the main organization and 10 competitors. This average is influenced by a few organizations with exceptionally large donor markets. The American Red Cross, which is consistently among the top five organizations in the campaign, has the largest donor-based market at 1,969 organizations. Row two indicates that an average of two out of the ten competitive organizations in these markets are in the same subsector, defined using the 26 NTEE major groups, as the main organization. On average, an organization in the CFC receives about 7 percent of the gifts in its market. The markets receive an average of $210,675 gifts per year, and this average is once again influenced by a few particularly large organizations that also have large markets. The final three rows of Table 25 show that the organizations in the CFC receive, on average, 153 donations totaling $1,293 in each zone and year. On average, 26 percent of an organization's donations are from donors who give to only one nonprofit.

Table 25. Summary Statistics on Organizations and Their Markets

	Mean	Sd	Min	Median	Max
Market Characteristics					
Number in donor-based mkt	11.5	(28.7)	1.0	5.0	1,969.0
Number of donor-based mkt in same subsector	1.7	(4.2)	0.0	1.0	276.0
Organization’s share of its market	0.07	(0.13)	0.00	0.02	1.00
Total pledges to organization’s market (2011 $)	210,675	(1,360,550)	3	15,220	39,835,868
Organization Characteristics					
CFC pledges to organization (in 2011 $)	1,293	(7,787)	0	315	1,247,797
Number of gifts to organization	153	(502)	1	42	10,827
Proportion of gifts non-contested	0.26	(0.16)	0.00	0.26	0.97

Note: N=171,842. Organization and market data is at the organization-zone-year level. Standard deviations in parentheses. Zeros in minimum column are due to rounding in rows 3 and 5.

As suggested by Table 25, there is some overlap between the donor-based market and traditional subsector markets. Table 26 shows how market size and market overlap vary by subsector. Row 1 describes the subsector markets. For organizations in the CFC, the subsector market would include an average of 212 organizations when subsector is defined using 12 NTEE groups. This is much larger than the 11.5 organizations, on average, in the donor-based markets, which are described in Row 2. Using the subsector market definition, health, human services, and international organizations have the largest markets, on average, because these types of organization have strong participation in the CFC. Using the donor-based market definition, hospitals have the largest markets, on average. This is influenced by the fact that the few hospitals participating in the CFC are quite popular. Examples include St. Jude Children’s Research Hospital and Shriners Hospitals for Children. On average, there is relatively low overlap between the subsector market definition and the donor-based market definition. This is perhaps surprising, given the importance that the nonprofit research tends to place on the subsector definition of nonprofit competitive markets. On average, an organization can expect that 3.2 of its 10.5 competitors, or 30 percent, will share its 12-group subsector. The percent of overlap varies somewhat by subsector. Higher education organizations have particularly low overlap between the subsector and market definitions, which is intuitive if one believes that most individuals attended and give to only one college and therefore very few colleges would share donors.

Table 26. Market Overlap

	All	AR	BH	ED	EH	EN	HE	HU	IN	MU	PU	RE	UN
Avg Number in Subsector Mkt	212.1	44.5	8.3	70.9	8.8	127.0	286.0	308.0	185.3	6.0	146.9	50.6	33.7
	(162.3)	(44.2)	(14.1)	(70.2)	(4.1)	(61.9)	(130.0)	(207.6)	(107.4)	(13.6)	(79.1)	(33.6)	(61.2)
Avg Number in Donor-based Mkt	11.5	10.8	15.3	8.9	26.9	13.1	11.1	12.8	9.3	9.0	11.0	8.5	21.1
	(28.9)	(34.1)	(95.5)	(21.0)	(67.0)	(29.4)	(25.5)	(32.8)	(25.7)	(10.4)	(26.0)	(15.1)	(47.0)
Avg Overlap of Market Definitions	3.2	0.9	0.1	0.6	0.4	4.3	4.3	4.1	2.1	0.1	2.0	1.3	0.0
	(7.5)	(2.4)	(0.4)	(1.8)	(0.9)	(8.0)	(8.5)	(10.0)	(4.9)	(0.3)	(4.0)	(2.3)	(0.0)

Note: Standard deviations in parentheses. Data at the organization-zone-year level. Columns are 10 major groups of nonprofit activities: Arts, culture, and humanities (AR), higher education (BH), education (ED), hospitals (EH), environment and animals (EN), health (HE), human services (HU), international, foreign affairs (IN), public, societal benefit (PU), religion related (RE), mutual/membership benefit (MU), and unknown (Z). Row 1: Average number of organizations in the traditional subsector markets. Row 2: Average number of organizations in the donor-based market. Row 3: Average number of organizations in the donor-based market that would have been in the traditional subsector market as well. Subsectors used for the traditional markets are the 25 major NTEE groups plus Hospitals and Higher Education.

In contrast, the health subsector has very high overlap between the two definitions, with approximately 38 percent of donor-based market organizations appearing in the subsector market as well.

Overlap between donor-based markets and traditional subsector markets can also be analyzed by looking at the network ties and a more granular nonprofit subsector definition. A tie between two organizations means that the organizations are in the same market. Ties between organizations in the same NTEE major group, which includes 27 categories, occur 14.7 percent of the time.[29] Table 27 shows the prevalence of same-subsector ties, by subsector. Same subsector ties are most prevalent among animal-related organizations (31.2 percent), followed by disease-related organizations (22.4 percent) and international-focused organizations (22.2 percent).

[29] Ties between organizations in a less granular 12-category grouping occur 28.3 percent of the time, and 38.9 percent of ties are between organizations in the same 5-category NTEE group.

Table 27. Proportion of Market (Network Ties) In Same Subsector

Subsector	Proportion Market in Same Subsector
A - Arts, Culture, & Humanities	0.082
B - Education	0.063
BH - Higher Education	0.003
C - Environment	0.139
D - Animal Related	0.312
E - Health Care	0.083
EH - Hosptials	0.014
F - Mental Health and Crisis Intervention	0.058
G - Diseases, Disorders, & Medical Disciplines	0.224
H - Medical Research	0.153
I - Crime & Legal-related	0.040
J - Employment	0.007
K - Food, Agriculture, & Nutrition	0.041
L - Housing & Shelter	0.042
M - Public Safety, Disaster Preparedness, & Relief	0.012
N - Recreation & Sports	0.062
O - Youth Development	0.056
P - Human Services	0.166
Q - International, Foreign Affairs, & National Security	0.222
R - Civil Rights, Social Action, & Advocacy	0.103
S - Community Improvement & Capacity Building	0.015
T - Philanthropy, Voluntarism, & Grantmaking Foundations	0.052
U - Science and Technology	0.024
V - Social Science	0.022
W - Public & Societal Benefit	0.099
X - Religion-related	0.150
Y - Mutual & Membership Benefit	0.007
Total	0.147

Note: Table reports the overall proportion of market organizations (network ties) that are in the same subsector. Subsectors are the 25 major NTEE groups plus Hospitals and Higher Education.

Given the evidence presented here that many of the donor-based market competitors are not in the same subsector, a natural question arises: just what kinds of organizations are the other-subsector competitors? In many cases, the competitors are intuitive. For instance, Special Olympics is categorized as a “Recreation and Sports” organization. However, its most important competitors are in the “Diseases, Disorders, and Medical Disciplines” subsector and the “Health Care” subsector. Donors that give to Special Olympics rarely give to other sports organizations, but they often give to organizations like the National Down Syndrome Society, St. Jude Children’s Research Hospital, the Children’s Miracle Network, the National Down Syndrome Congress, and the Ronald McDonald House Charities. As another example, the ACLU’s competitors tend to be other quintessentially liberal causes. Even though the ACLU is categorized as a “Civil Rights, Social Action, and Advocacy” organization, its competitors are often organizations in the subsectors of “Environment” and “International, Foreign Affairs, and National Security.” Organizations like Amnesty International, Doctors Without Borders, the Nature Conservancy, and the Sierra Club Foundation are important competitors in these subsectors. In addition, National Public Radio, an “Arts” organization, and Planned Parenthood, a “Health Care” organization, are important competitors for the ACLU. These examples demonstrate that the donor-based market definition yields lists of competitors that are intuitively appealing.

2.7.3 Validation of market definition

For the donor-based market to be an improvement over the subsector market, donor-based markets not only must be intuitively appealing, but also must capture the true set of nonprofit organizations that are considered by a donor. If donor-based markets capture substitution patterns better than subsector markets, then this is a strong argument that the donor-based market is valid and preferable to the subsector market. To test this, I analyze donor substitution between nonprofits after an unexpected change to the CFC's nonprofit list. It is important that the change be unexpected, or exogenous, to decrease the probability that a donor is changing their donations because the donor has changed his or her ideal point on the nonprofit product space. The CFC data includes cases when a nonprofit drops off the list of eligible organizations. In the year of the disappearance, many donors increase their giving to one of the remaining organizations in their giving set or begin giving to an entirely new organization. If the donor-defined market captures the true substitution set, then many of these new gifts should be in the list of network neighbors in the previous year.[30] If the subsector market captures the true substitution set better, then more of the organizations should be in the subsector market.

To assess the extent to which each market definition predicts substitution, I

[30] In such a case, it is also possible that the donor begins giving to the organizations outside of the CFC. However, this should not bias the analysis. The analysis focuses on donors who begin giving to a new CFC organization after one of their preferred organizations drops out of the CFC. If the donor simply begins giving outside of the CFC rather than giving to a different CFC organization, then they would not appear in the list of substituting donors.

created a list of organizations that disappear from the CFC. I include both organizations that permanently disappear and those that disappear temporarily. I exclude disappearances that happen in merger years and may therefore be endogenous (bad communication, etc.). I then find the donor records[31] associated with those gifts. I exclude donor records from my analysis when more than one organization the donor was giving to disappears, because I will not be able to tell which new organizations are substitutes for which older organizations. I also exclude donor records when the donor decreases or quits giving to an organization that does not disappear. Unprompted changes in giving behaviors indicates that an individual may have shifted his or her ideal position in the product space, so these donors should be excluded from the analysis. These criteria allow me to increase my confidence that the substitution is related to the disappearance of the specific disappearing organization, rather than other factors.

The first panel of Table 28 shows that 38% of substitutions are found on the previous year's donor-based market, which is the immediate (first-degree) network neighbors list. The second panel shows that the percentage of substitutions predicted increases to 73% when second-degree network neighbors are also included in the list.

[31] Excluding those "users" that appear to include gifts for multiple people.

Table 28.Validation: Donor-based Markets and Substitution from Disappearing Organizations

Panel A: First Degree Neighbor Markets

	2009	2010	2011	2012	Total
In Donor-based Market	34.3	35.1	41.5	35.7	37.7
Not in Donor-based Market	65.7	64.9	58.5	64.3	62.3
Total	100.0	100.0	100.0	100.0	100.0
	(35)	(94)	(205)	(207)	(541)

Panel B: Second Degree Neighbor Markets

	2009	2010	2011	2012	Total
In Donor-based Market	68.6	62.8	72.2	77.8	72.5
Not in Donor-based Market	31.4	37.2	27.8	22.2	27.5
Total	100.0	100.0	100.0	100.0	100.0
	(35)	(94)	(205)	(207)	(541)

Note: After an organization quits the CFC, donors who were giving to that organization choose a new nonprofit to contribute to. Tables report if this new nonprofit was in the competitive market defined using the donor-based method. The first row reports the percent of donor substitutions that were predicted by the donor-based markets from the previous year. First panel defines competitive markets using immediate network neighbors. Second panel differs by including organizations in the competitive market that are second-degree network neighbors (organizations that share a common neighbor). Parentheses are column total observations.

The first panel of Table 29 shows that 24% of substitutions are within the same 27-group NTEE subsector. This 27-group categorization of nonprofits is a relatively broad competitive definition. Some research on competition even defines the relevant market at a level below this (the NTEE-CC code), which includes hundreds of categories. Defining markets using NTEE-CC codes would capture an even lower percentage of donations than the 27-group NTEE subsectors. The second panel of Table 29 shows that the subsector markets must be aggregated up to the 12-group level to achieve a level of accuracy similar to the donor-based market definition. The relative success of the 12-group subsector market at capturing substitutions is unsurprising, since these markets include hundreds of organizations. When a market is so large, it can predict many substitutions by random chance.

Table 29. Validation: Subsector Markets and Substitution from Disappearing Organizations

Panel A: Twenty-six Sector Markets

	2009	2010	2011	2012	Total
In Subsector Market	8.8	25.8	20.3	28.7	23.8
Not in Subsector Market	91.2	74.2	79.7	71.3	76.2
Total	100.0	100.0	100.0	100.0	100.0
	(34)	(89)	(187)	(202)	(512)

Panel B: Twelve Sector Markets

	2009	2010	2011	2012	Total
In Subsector Market	26.5	41.6	39.6	43.6	40.6
Not in Subsector Market	73.5	58.4	60.4	56.4	59.4
Total	100.0	100.0	100.0	100.0	100.0
	(34)	(89)	(187)	(202)	(512)

Note: After an organization quits the CFC, donors who were giving to that organization choose a new nonprofit to contribute to. Tables report if this new nonprofit was in the competitive market defined using the subsector method. The first row reports the percent of donor substitutions that were predicted by the subsector markets from the previous year. First panel defines subsector markets using 26 NTEE subsectors (major groups). The second panel aggregates these groups into 12 larger NTEE categories. Parentheses are column total observations. Missing values arise when sector is not found.

The donor-based does a better job than the subsector market at predicting actual donor substitutions under exogenous conditions. This is true even though the average subsector market includes many more competitors than the average donor-based market.

The fact that the larger subsector markets are not capturing substitution patterns means that these markets contain many organizations that are not true competitors and miss organizations that are true competitors. Any measures of competition intensity derived using the subsector markets are likely to be flawed and may lead to erroneous conclusions about the relationship between competition and nonprofit behaviors. The next section explores this possibility in the context of the CFC.

2.8 Competition and Overhead Application

In this section, I examine an important nonprofit policy issue—the relationship between competition and nonprofit spending on overhead—and compare the results obtained from the subsector and donor-based market definitions. The CFC provides a good context for this application for several reasons. First, because the CFC includes individual data and information on nonprofits' subsectors, it can be used to define both donor-based markets and subsector markets. Second, the CFC data are longitudinal, allowing me to control for unobserved factors, provided they do not vary over time. Finally, the CFC makes overhead information readily available, making it a salient characteristic for both donors and nonprofit leaders.

This section proceeds in three parts. First, I describe the method of analysis for the application. I define how I will calculate the main variables of interest, overhead rate and competition intensity. I also describe the OLS model employed in the analysis. Second, I show an explanatory scatter plot exploring the relationship between competition intensity and overhead rate in the CFC data. Third, I present the results from the two regressions. Finally, by comparing results obtained with the two market definitions, I discuss how a new market definition can change researchers' understanding of competition among nonprofit organizations.

2.8.1 Application method of analysis

To use CFC data to understand the relationship between competition and overhead, and to compare the results of the analysis when using different market definitions, the data need to be converted from individual-level giving records to organization-level data with measures of competition intensity. For each organization, I begin by constructing its subsector market and its donor-based market. These markets are identical those analyzed in Section VI.[32] I use the 26-group subsector market here to increase the power of the analysis.

Next, I calculate a measure of competitive intensity for both the subsector market and the donor-based market. To calculate the competitive intensity for organization *i*, I use the Herfindahl-Hirschman Index (HHI). As discussed in Section III, the HHI is an index of market concentration and is also the most commonly used method of measuring competition intensity in the nonprofit literature. In markets with low HHI values,

[32] Most donors in the data are straightforward, and give only one online pledge (which may include several gifts) using a specific donor ID. Paper pledges, which also may include several gifts, do not have a donor ID. I assume each paper pledge is a separate donor (although in theory one person could turn in multiple paper pledges). In contrast, if an online donor has multiple pledge records in the same year under the same donor ID, I count those as one pledge.

donations are spread among many organizations, while in markets with high HHI values donations are concentrated among very few organizations. HHI values range from 0 to 10,000, with 10,000 indicating that an organization has a monopoly within the market.

HHI for organization *i* is calculated by taking the sum of the squared market shares (σ_j) for each organization in *i*'s market, including *i*. Market shares are calculated for each organization in organization *i*'s market. An organization's market share is its own observed CFC donations divided by the total observed CFC donations for all organizations in *i*'s market. Only donations in that zone in that year are used. Shares are rounded to the nearest whole percent, so the final HHI values are integers from 0 to 10,000.[33] The formal representations of these definitions are given below, with subscripts for zone and year eliminated for readability.

$$HHI_i \equiv \sigma_i^2 + \sum_{j=1}^{n} \sigma_j^2 \, , \; j \neq i \qquad (2)$$

$$\sigma_i \equiv \frac{Donations_i}{Donations_i + \sum_{j=1}^{n} Donations_j} \, , \; j \neq i \qquad (3)$$

Differences between the HHI calculations for the subsector markets and the donor-based markets occur more because of the differences between the market definitions than from the way the HHI is calculated. Calculating the HHI for the subsector markets is straightforward. Subsector markets will be identical for all

[33] The Gini coefficient is also used as an index of nonprofit concentration (for instance in Seaman 2014), although it is uncommon. Seaman et al. make the case that observing the HHI and Gini coefficient together can better categorize market types. Analysis of the Gini coefficient is left for future work.

organizations with the same NTEE code, the same zone, and the same year. Using the CFC donations within a particular zone and year, I calculate the share of donations directed to each organization in the subsector and calculate the HHI using the standard formula. Because the included organizations and shares are the same, all organizations in a subsector will have the same HHI value for a particular zone and a particular year.

The HHI for the donor-based market is also calculated using the standard formula. The difference with this market definition is that the CFC donation shares are calculated using the specific competitors in an organization's market. Every organization has a unique market, and so the shares that are input into the HHI equation will be different for each organization.

To calculate overhead, I use the administrative and fundraising expense rate (AFR) directly from the CFC data. My data only include this information for national organizations, so models with AFR include only the approximately 2,000 to 2,500 national organizations participating in each year. To calculate AFR, an organization is instructed to use information from its IRS Form 990.[34] The AFR, which is expressed as a percentage, is:

$$AFR_i \equiv \frac{Management\ and\ General\ Expenses_i + Fundraising\ Expenses_i}{Total\ Revenue_i} \times 100 \quad (4)$$

[34] The rule states, "Add the amount in Part IX (Statement of Functional Expenses), Line 25, Column C (Management and General Expenses) to the amount in Line 25, Column D (Fundraising Expenses), and divide the sum by Part VIII (Statement of Revenue), Line 12, Column A (Total Revenue)." For more information, see: https://www.opm.gov/forms/pdf_fill/opm1647a.pdf

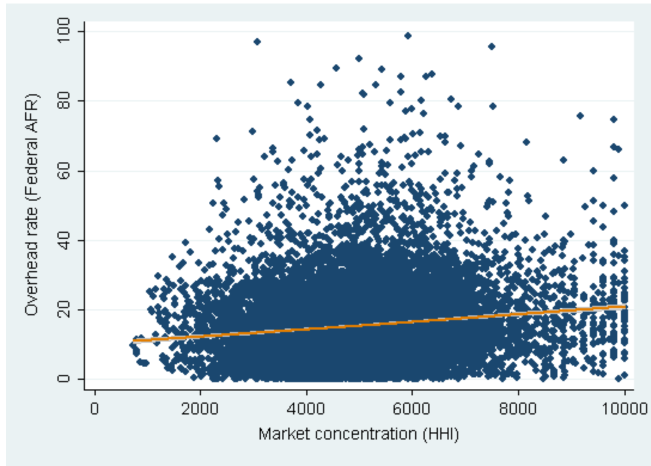
Like other measures of overhead in the nonprofit literature, the AFR is not without its faults. Overhead measures relying on IRS 990 reporting have been shown to be subject to misreporting, especially underreporting by nonprofits that know donors prefer low overhead rates (Wing et al. 2006). However, this is the best measure of overhead rate available for the nonprofit sector at this time.

2.8.2 Exploratory scatter plots

The two scatter plots in Figure 12 show the relationship between HHI and overhead rate, by market definition. In each plot, the X-axis is the level of market concentration, represented by the HHI index. Organizations with a HHI of 0 face the strongest competition, and organizations with a HHI of 10,000 face the weakest competition. The Y-axis is the AFR overhead rate, with a lower number indicating a lower percent of revenue spent on administration and fundraising.

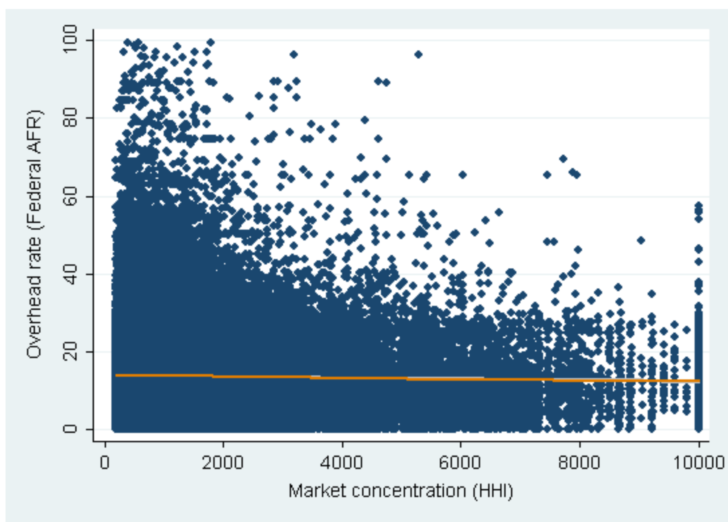
The first graph depicts the overhead rate and the HHI calculated using the donor-based markets. The upward slope of the line of best fit in the graph indicates that the average AFR overhead rate tends to rise as the HHI increases. Because higher HHI scores tend to indicate lower competition, this result suggests that more competition is related to lower overhead rates. The second graph depicts the overhead rate and the HHI calculated using the subsector markets. In this graph, the line of best fit does not show a clear relationship between overhead and HHI.

Panel A: Donor-based Market Definition



Note: Years 2008 through 2013 are included. Organizations without gifts are excluded from the graph. Only organizations in the individual data are included.

Panel B: Subsector Market Definition



Note: Years 2008 through 2013 are included. Subsector is defined using 26 NTEE subsectors. Only organizations in the individual data are included.

Figure 12: Correlation Between Market Concentration (HHI) and Overhead, by Market Definition Procedure

2.8.4 OLS regressions

To understand the effect of competition on an organization's overhead rate, I use the panel nature of the data to run an OLS model with organization and time fixed effects. The model is shown in Equation 5.

$$Overhead_{it} = \alpha + \beta_1 HHI_{it-1} + \beta_2 Controls_{it} + \delta Org_i + \gamma Year_t + \epsilon_{it} \quad (5)$$

The organization fixed effects account for any characteristics of the nonprofit that persist over time and lead to a consistently higher or lower overhead rate. These characteristics might include the sector, the year the nonprofit was founded, or the headquarters location. The year fixed effects account for events that take place in a specific year and might cause all nonprofits to experience a higher or lower overhead rate. These events might include financial shocks, like the state of the stock market or the Great Recession. This model results in an identification strategy that relies on changes in competition faced by each individual nonprofit over time.[35]

The measure of competition, HHI, is lagged to allow time for overhead to respond to competition. The included controls are parsimonious, and include only the total revenue of the organization at time *t*, total contributions from all sources at time *t*, and

[35] The changes in competition faced by each nonprofit are a function of changes in donor decisions. These decisions are driven by all the organizations' attributes, the donors' attributes, and the attributes of competing organizations. To the extent that these attributes are also driving total giving to the organization, they should be captured in the coefficient on the total organizational revenue. Including this variable intuitively limits the bias due to time-varying omitted variables that are correlated with the decisions.

percent of revenues form contributions at time *t*.[36] Each of these measures comes from the IRS Form 990 data, as reported in the NCCS Core Files.

Table 30 presents the regression results when the HHI is calculated using the donor-based market definition. The results are presented using four models, with the final model being the preferred model presented in Equation 5. The first model is similar to the first scatter plot from Figure 12, and documents the correlational relationship between HHI and overhead. The coefficient indicates that as HHI increases by one point, the overhead rate increases by 0.0001 percentage points. Since the median overhead rate in the data is 14 percent, this is a small increase. The positive sign on the coefficient indicates that the average overhead rate tends to rise as the HHI increases. Because higher HHI scores tend to indicate lower competition, this result suggests that less competition is correlated with higher overhead rates. The positive and significant coefficient on HHI persists, even after controlling time-varying financial variables in the second model, and common shocks to all organizations in a particular year in the third model. In the fourth model, which is the preferred model from Equation 5, I find that a one-point increase in the HHI leads to a 0.00002 percentage point increase in overhead

[36] Previous research has identified several organization-level factors that are related to nonprofit overhead rates. Lecy and Searing found that overhead rates vary based on an organization's size and subsector (2015). The present study includes annual revenue, which is a measure of organization size, as a control variable. Organization subsector is not included, because subsector tends to be constant over time. Subsector is therefore captured by the organization fixed effects. Ecer et al. find that size, age, sources of revenue, and the share of earned income are related to overhead rates in the nonprofit sector (2017). Age, like subsector, does not vary within an organization and so is excluded from the present analysis. The dollars from contributions and the proportion of revenues from contributions are the closest measures available from the nonprofit financial database used in the present study, so these are the two variables included as controls here.

rate. The magnitude of the result is easier to interpret for larger increases in HHI. An organization that experiences a 1000-point increase in HHI, which is roughly the difference between the 25th percentile and the 50th percentile of the distribution, is expected to increase overhead by 0.02 percentage points. It is important to note that, unlike the first three models, the coefficient on HHI in the fourth model is not significant at the $p<0.05$ level, although it is at the $p<0.1$ level ($p=0.07$).

Table 31 shows that the organizations with low overhead tend to be less responsive to changes in competition than organizations with high overhead. The first four columns repeat the analyses from Table 30, but only for the organizations with lower-than average overhead. None of the results are significantly different from zero. Low overhead is defined as overhead below the median value of 12.4 percent. The second four columns repeat the analyses with high-overhead organizations. These organizations tend to be responsive to changes in overhead, although the coefficient on HHI for the preferred model is still not significantly different from zero at the $p<0.05$ level ($p=0.057$).

Table 32 presents the regression results when the HHI is calculated using the subsector market definition rather than the donor-based market definition. While the first correlational column is non-significant, the second and third models presented both yield significant and negative results. If these results are to be believed, then a one unit increase in HHI decreases the overhead rate by 0.0002 percentage points. A 1000-unit increase in HHI would decrease the overhead rate by 2 percentage points. The negative coefficient on the results indicates that higher HHI values, which are associated with lower competition, lead to decreases in the overhead rate. This would mean that organizations in more competitive environment are spending more on management or fundraising expenses, perhaps because the organizations are advertising heavily to attract donors. The final model in Table 31, which is the preferred model, is positive but very close to zero. From this result, organizations are not predicted to change their overhead in response to changes in competition.

A researcher would make different conclusions about the relationship between competition and overhead if she were to use the subsector markets rather than the donor-based markets to calculate competitive intensity. Using the subsector market definition appears to bias the results downwards in this case.

Table 30. Regressions of Overhead on Market Concentration, Donor-based Market

	(1) Basic	(2) With controls	(3) YR FE	(4) Org+YR FE
HHI of organization's market (lagged)	0.000145*	0.000201*	0.000205*	0.0000219
	(0.0000708)	(0.0000896)	(0.0000901)	(0.0000119)
Annual revenues (in $)		4.68e-09	4.68e-09	9.01e-09
		(3.66e-09)	(3.66e-09)	(6.77e-09)
Annual contributions (in $)		-9.59e-09	-9.51e-09	-1.65e-08*
		(5.86e-09)	(5.83e-09)	(7.43e-09)
Proportion of revenue from contributions		11.32	11.30	27.44***
		(7.276)	(7.256)	(6.106)
Observations	37598	32515	32515	32515
Adjusted R^2	0.000	0.062	0.065	0.858

Note: * p < 0.05, ** p < 0.01, *** p < 0.001. Robust standard errors, clustered at the organization level. The unit of observation is organization-market-year. Only national organizations included. Organization revenues and contributions are the CPI-adjusted revenues on the Form 990 for all submitted forms for periods between July 2006 and October 2012. The measure of concentration (HHI) is coded is coded such that an increase in the measure represents a decrease in competition. The measure is lagged by one year.

Table 31. Regressions of Overhead on Market Concentration, by Level of Overhead, Donor-based Market

	Low Overhead				High Overhead			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Basic	With controls	YR FE	Org+YR FE	Basic	With controls	YR FE	Org+YR FE
HHI of organization's market (lagged)	0.0000322	0.0000449	0.0000457	0.00000691	0.000140	0.000192*	0.000198*	0.0000290
	(0.0000306)	(0.0000335)	(0.0000337)	(0.00000827)	(0.0000727)	(0.0000806)	(0.0000813)	(0.0000152)
Annual revenues (in $)		1.57e-09*	1.56e-09*	9.85e-09**		2.25e-08*	2.24e-08*	4.03e-08
		(7.21e-10)	(7.18e-10)	(3.39e-09)		(1.02e-08)	(1.02e-08)	(2.61e-08)
Annual contributions (in $)		-2.43e-09	-2.39e-09	-1.29e-08**		-3.24e-08*	-3.20e-08*	-6.33e-08
		(1.70e-09)	(1.71e-09)	(3.94e-09)		(1.26e-08)	(1.25e-08)	(3.51e-08)
Proportion of revenue from contributions		-0.152	-0.152	12.88*		19.74*	19.70*	32.09***
		(1.558)	(1.556)	(5.033)		(7.677)	(7.664)	(4.425)
Observations	18698	16021	16021	16021	18900	16494	16494	16494
Adjusted R^2	0.000	0.005	0.006	0.819	0.000	0.217	0.219	0.858

Note: * p < 0.05, ** p < 0.01, *** p < 0.001. Robust standard errors, clustered at the organization level. High overhead is defined as AFR¿=12.4 percent. The unit of observation is organization-market-year. Only national organizations included. Organization revenues and contributions are the CPI-adjusted revenues on the Form 990 for all submitted forms for periods between July 2006 and October 2012. The measure of concentration (HHI) is coded is coded such that an increase in the measure represents a decrease in competition. The measure is lagged by one year.

Table 32. Regressions of Overhead on Market Concentration, Subsector Market

	(1) Basic	(2) With controls	(3) YR FE	(4) Org+YR FE
HHI of subsector market (lagged)	0.000143	-0.000181**	-0.000183**	0.00000818
	(0.000130)	(0.0000617)	(0.0000611)	(0.0000306)
Annual revenues (in $)		5.74e-10	5.66e-10	-8.18e-09***
		(5.44e-10)	(5.39e-10)	(2.29e-09)
Annual contributions (in $)		-2.46e-09*	-2.43e-09*	3.81e-09
		(1.03e-09)	(1.02e-09)	(2.61e-09)
Proportion of revenue from contributions		1.482	1.485	2.992
		(1.201)	(1.196)	(2.183)
Observations	36632	32086	32086	32086
Adjusted R^2	0.000	0.008	0.010	0.712

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors, clustered at the subsector-zone-year level. The unit of observation is organization-market-year. Only national organizations included. Organization revenues and contributions are the CPI-adjusted revenues on the Form 990 for all submitted forms for periods between July 2006 and October 2012. The measure of concentration (HHI) is coded is coded such that an increase in the measure represents a decrease in competition. The measure is lagged by one year.

2.9 Conclusions

The present paper introduces and validates a new empirical market definition procedure for the nonprofit sector. The work contributes to the literature on nonprofit competition in several important ways. It is the first paper to use donor-level data to define the donor-based market for nonprofit organizations, rather than relying on the organization's subsector and geographic location. It uses actual substitutions made when organizations quit the CFC to validate this measure, showing the donor-based market definition predicts substitutions better than the sector-based market definition does. It also shows that conclusions about important policy issues, such as how nonprofits change their overhead spending in response to increases in competition, can be influenced by the market definition selected.

This result must be carefully interpreted due to some of the limitations of this study. The current market definition and measure of competitive intensity could miss competitors in smaller zones. In zones where fewer donors are observed, the present method could miss some competitors. The problem also would exist if donors were too similar and were not covering the full nonprofit product space. Without a sufficiently large and diverse donor sample, the donor-based market definition may miss competitors. This problem could be solved with additional data or with a more advanced network model. A more nuanced understanding of competition could be developed using a network model that acknowledges that the observed donations are a sample and that the resulting network is subject to sampling variability. However, this is beyond the scope of the current paper, and is left for future work.

Future work could also identify the causal connection between competition and overhead in a stronger way. Hypothetically, the current results could be affected by unobserved, time-varying factors that are correlated with both competition and overhead. Research that incorporates an exogenous shock to competition would mitigate these concerns.[37] In the absence of such a shock, the addition of additional time-varying covariates could better identify the effect of interest.

Finally, future work could implement or develop different measures of competitive intensity to be used with the donor-based market definition and individual giving data. While the HHI is an important and often-used measure of competitive intensity, it can generally be implemented with only organization-level data and does not use the individual-level data available. Using the individual donation data could allow for new measures of competitive intensity. For example, with the individual-level data, one can observe what proportion of an organization's donors give only to that organization and what proportion of the donors split their giving among two or more organizations. When more of an organization's donors split their giving, the organization is arguably

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[37] The exogenous shock used in the market validation procedure is not suitable for this analysis. The market validation procedure uses individual-level data, while the regression analysis uses organization-level data. The number of organizations which disappear from the CFC is limited, and so this exogenous shock does not provide the necessary power for the regression analyses.

more exposed to the competitive market. This observation could be used to develop a new measure of market exposure that could contribute to our understanding of competition in the nonprofit sector.

The findings in this paper regarding the scope of nonprofit competition and the character of nonprofit competitors have important implications for research. Understanding competition in the nonprofit sector is important to a wide variety of research questions. Each of these questions relies on an accurate definition of the market and of the level of competitive intensity. Going forward, researchers should prioritize the development of new and more accurate ways to measure nonprofit competition.

Finally, the findings in this paper also have implications for the way nonprofit leaders understand their competitive markets. The nonprofit leader described in this paper’s introduction was associated with a dog rescue organization and was trying to determine which other organizations are competitors. The research presented here suggests that the leader should not automatically consider only organizations that produce similar services to be competitors. Instead, the leader should survey the dog rescue organization’s donors to determine what other organizations the donors are contributing to. Then, she can focus the dog rescue’s competitive strategy on this donor-defined competitive market.

3. Chapter 3: Efficiency Among Nonprofit Intermediary Service Providers – Fundraising Before and After Government Service Area Consolidation in the Combined Federal Campaign

3.1 Overview

Nonprofit organizations in the United States provide a wide array of services on behalf of the government. In these situations, determining the optimal structure of the system is important—should more providers deliver services across smaller areas to increase local tailoring or should fewer providers deliver services across larger areas to take advantage of economies of scale? The answer depends on the tradeoffs between production efficiency and consumption efficiency. This paper examines nonprofit intermediaries implementing the Combined Federal Campaign (CFC), the workplace giving program for federal employees. I use a difference-in-differences analysis and nearly random consolidation timing to identify the effect of program structure on costs, fundraising outcomes, and fundraising efficiency. Surprisingly, I find that consolidated service areas experienced a decrease in average giving as well as a statistically insignificant decrease in average program costs. Combined, these effects yield no change in costs per dollar raised; the benefits of consolidation are more modest than CFC administrators had hoped.

3.2 Introduction

Government entities at all levels rely on external producers, such as nonprofit organizations, to deliver services. When government contracts with nonprofit service providers, it is important to optimize the structure of the contracting system. Each structure has potential advantages. If many nonprofit providers deliver government services within small geographic areas, the nonprofits may maximize local knowledge and tailor their services to local needs. Or, if fewer nonprofit providers deliver government services across larger geographic areas, the nonprofits may minimize costs and take advantage of economies of scale. The present paper examines how contract structures impact the efficiently of nonprofit service delivery, but the findings have implications regarding nonprofit efficiency and government contracting efficiency in general.

Questions like this, which examine the benefits of various industry structures, are familiar to students of microeconomics and industrial organization. In these fields, the analysis would focus on tradeoffs between production efficiency and consumption efficiency. Production efficiency requires minimizing long-run average costs. If there are economies of scale, then long-run average costs could be decreased by combining the inputs of two small firms into one large firm. An industry where firms experience economies of scale would achieve greater production efficiency with fewer, larger firms, all else equal. The same could be said for combining small nonprofits or consolidating contracts between the government and nonprofit service providers.

Consumption efficiency is achieved when each individual can consume the product they most prefer or where no one can consume a product he prefers more without forcing another person to consume a product she prefers less. A fundamental assumption is that consumers are heterogeneous and prefer heterogeneous products. Another possibility is that consumers are the same within a service area (such as a city) but differ between cities. In this case, consumption efficiency is achieved either when each city has a customized product or when no city can be given a better product for its needs without another city being given a product that is worse for that city's needs.

A tension exists between these two types of efficiency in the classical economic world of firms and consumers as well as in the world of government contracting. Customizing products and increasing consumption efficiency often means producing items in smaller batches and losing the advantages of economies of scale. Likewise, contracting with smaller service providers that can provide services customized to the local community means duplicating fixed costs, thereby diverting money that could have been spent serving more clients. In both scenarios, the goal is to maximize social welfare by combining inputs to produce the amount *and* combination of goods that maximize overall utility. Early scholars on government service delivery, contracting, and public choice noted similar tradeoffs. Bish and Warren (1972) argue that the structure and scale of government service delivery should be chosen based on two criteria: production efficiency and responsiveness to the preferences of citizens.[38] They argue that, local and sublocal government structures are preferable when services can be tailored to more uniform preferences of these smaller units. Although the authors are writing about direct government service provision rather than indirect service provision through contracts, their work also applies in the latter context when the contracted service can be tailored to local preferences.

In this work, I focus on the structure of contracting within the Combined Federal Campaign (CFC)—the nation's largest workplace giving campaign. Although casual observers may not immediately consider the CFC to be a government service, it is. The service the government is providing in this case is the opportunity for federal workers to give. Furthermore, the structure of the CFC is similar to that of many government services. The federal government contracts with one nonprofit organization, such as a United Way, in each local administrative zone to run the campaign. The nonprofit engages in a variety of activities (producing materials, organizing volunteers, processing paperwork) to serve the program's clients, which in this case are charitable federal government workers within the local administrative zone.

The CFC's local administrative zones have consolidated over time. In 2004, there were 313 service areas; by 2013, there were 163. The CFC's consolidation pattern makes

[38] See also Ostrom and Ostrom 1977. Later work lends less attention to diverse preferences. Both researchers and administrative decisionmakers have tended to emphasize production efficiency in general, and economies of scale more specifically (Boivard 2014).

it possible to examine the effect of fewer, larger service areas on efficiency. In the case of the CFC, I measure production efficiency using fundraising costs per employee solicited. This is the appropriate measure as solicitations are the “product” that the government is contracting with the nonprofit intermediaries to produce. To measure consumption efficiency, I would ideally want to understand employee utility per solicitation. With the data available, I instead measure contributions per employee. I decompose the contributions-per-employee measure into participation and contributions per donor[39]. I also measure contributions to local nonprofits per employee, because encouraging the inclusion of an attractive selection of local nonprofits is a way that the intermediary service providers can affect consumption efficiency. Finally, to summarize the two efficiency constructs, I analyze cost per dollar raised before and after the consolidations.

To understand the effects of service area consolidation on fundraising costs and giving, I perform a differences-in-differences analysis. The treated group in this analysis is the service areas that merge in a given year. The control group needs to be equivalent but untreated. Choosing the control group carefully will ensure that the measured effects are due to consolidating rather than other unobserved factors.

Non-consolidating service areas are not a good control group for service areas that consolidate. Service areas that consolidate are typically smaller and lower-performing

[39] Participation is equivalent to the proportion of employees who are donors or donors per employee. Contributions per employee is the product of contributions per donor multiplied by donors per employee. These two factors can also be described as the intensive and extensive margins.

than service areas that never consolidate. It is also likely that consolidating service areas are unobservably different than non-consolidating areas. Instead, I use service areas that consolidate in other years as the control group. I show that no statistically significant differences exist between the performance of zones that consolidate in the following year and zones that consolidate in other years. I also conduct a logistic regression to argue that, based on observed covariates, consolidation timing is as good as random.

Consolidation was associated with increases in costs per dollar raised. These increases are statistically insignificant, and economically small. The absence of efficiency gains is surprising, as it is not in line with the goals of consolidation in the CFC. The effect on costs per dollar raised is attributable to a decrease in consumption efficiency, as indicated by a statistically significant decrease in dollars pledged per employee after consolidation. The decrease in consumption efficiency is larger than the change to production efficiency. Production efficiency, measured as fundraising cost per employee solicited, decreases after consolidation, but the difference is small and statistically insignificant. Each of these effects seems to dissipate over time.

The present research contributes to the limited literature on the Combined Federal Campaign and to ongoing policy discussions about its future. Empirical analyses of the CFC are limited, and focus mostly on the role of overhead ratios (Bowman 2006) and other factors affecting employees' decisions to donate (LePere-Schloop and Christensen 2014). Existing research on workplace giving in general is also relatively sparse (Osili et al. 2011, Christensen et al. 2012, Nesbit et al. 2012, Shaker et al. 2014). No literature exists on the contracting structure of the CFC, even though it is an area of active policy change. In 2015, the CFC released a memo explaining that the OPM would mandate zone consolidations, reducing the number of active zones to 37. This consolidation is taking place in 2017.[40]

Although the CFC is not usually the first example of government-nonprofit contracting that comes to mind, the results presented here also contribute to this literature. While the CFC is unusual because it serves governmental employees rather than members of the public, the fundamental tradeoff between size and responsiveness that exists in the CFC is also present in other contracting arrangements. The outcomes of the CFC provide for an interesting, quantifiable, example of the two forces. Furthermore, the ability to observe change in scale "in real time" makes this a valuable example.

Understanding the consequences of CFC consolidation over time also provides important evidence about the relationship between the scale of nonprofit fundraising and performance. Policymakers, foundation leaders, and other thought leaders in the nonprofit sector have focused a great deal of recent attention on "scaling," a term used to represent the idea of increasing nonprofit organization size to a minimum efficient scale. In fact, one of the stated goals of the Social Innovation Fund, the grantmaking program of

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[40] The new zones were announced in CFC Memorandum 2015-01, released on January 20, 2015. On October 23, 2015, the new regulations were delayed until 2017. The OPM confirmed that the number of CFC administrative zones would be 37 at the 2017 CFC National Training, held on February 15, 2017.

the federal government's Corporation for National & Community Service, is "Scaling What Works" (2015). Furthermore, in a survey of nonprofit leaders, Mitchell (2015) finds that nonprofit leaders believe organizational size is important to nonprofit effectiveness. Unfortunately, there has been relatively limited scholarly work linking the scale of nonprofit operations and nonprofit efficiency or effectiveness, broadly defined. Jeff Bradach, a staunch advocate of scaling, states, "But big nonprofits are not a societal panacea: the jury is out on whether scaling organizations will translate into scaling impact" (Kim and Bradach 2012, p. 16).

The present research has the potential to inform the discussion relating scale and nonprofit efficiency. Specifically, understanding how consolidation affects fundraising efficiency in the CFC may tell us something about how other organizations' fundraising efficiency changes with scale. However, the present context cannot provide much information about how the program efficiency of nonprofits changes with scale. Most nonprofit organizations' programs involve public goods and social services that look quite different from the programs of the CFC, which are focused on providing opportunities for federal employees to donate. It is also important to note that the consolidations examined here are consolidations of government contracts, not organizations.[41] Therefore, direct analogies to nonprofit mergers should be avoided.

[41] Notably, the nonprofit organizations administering the CFC do not merge when two zones consolidate. The contracts are consolidated into one larger contract. This may be administered by one of the original organizations, or a new organization might win the contract.

The analysis proceeds as follows: Section II explains the existing literature related to changing the scale of government-nonprofit contract structures. Section III describes in more detail the consolidation of service areas in the CFC. It also explains the patterns of consolidation over this time period and discusses the theoretical effects of consolidation on campaign performance. Section III describes the data and the measures used to analyze campaign performance. It also explains how the analysis sample was constructed. Section IV describes the main analytical strategy as well as some of the robustness checks performed. It compares possible control groups, and explains that the best control group is zones that consolidated in earlier years, rather than zones that never consolidated. Section V provides the empirical results, and Section VI concludes.

3.3 Literature on Scale in Government Contracting and Nonprofit Organizations

The present paper examines how changes to the scale of government-nonprofit contract structures impact the efficiently of service delivery. Despite early scholars' attempts to draw attention to the tension between production and consumption efficiency in the context of direct government service provision (for instance Bish and Warren 1972), most research on indirect service provision has focused on production efficiency, as is discussed in this section. The focus on production efficiency in general, and economies of scale specifically, now seems to dominate the literature on both government contracting and nonprofit service delivery.

3.3.1 Economies of scale in contracting

In practice, increasing production efficiency in government contracting is often equivalent to decreasing costs, because the number of citizens who need to be served is held fixed. Theoretically, contracting should generate cost savings by introducing competition and by selecting providers that are better able than the state to choose the optimal scale of production (Bish and Warren 1972, Ferris and Graddy 1986).[42] Two examples illustrate how economies of scale might apply when services are provided by private contractors, such as nonprofits. First, there may be input price savings when services are produced at a larger scale. If nonprofit organizations provide services across many municipalities, they may achieve scale that would not have been possible for a government purchaser operating in only one city. Second, nonprofits may be able to smooth capacity utilization over time. If a government requires a certain type of service periodically (for 3 months per year, in the case of the CFC), it may have trouble decreasing labor and other inputs to production during the rest of the year. A nonprofit can be more flexible in managing inputs and avoid this issue (Ferris and Graddy 1986).

[42] One of the possible benefits of competition in a contracting situation is an increase in "X-efficiency" of workers. This is the idea that competition induces workers to exert more effort (Leibenstein 1966). Survey evidence seems to indicate that increases in x-efficiency occur in the context of government outsourcing, although this methodology has been criticized (Jensen and Stonecash 2005). Other research looking for evidence of cost savings from contracting out is mixed (Bel et al. 2010, Boyne 1998, Hirsch 1995). This has led to the theory that the true purpose of contracting is related to political goals such as satisfying interest groups or offloading the political risk of service delivery onto contractors (Van Slyke and Roch 2004). There is some evidence that intergovernmental cooperation may generate more cost savings than contracting out (Bel and Warner 2015, Bel et al. 2006).

Early research investigates the extent to which this economy of scale argument holds in a limited way. The research presents empirical evidence comparing price per unit for a monopoly contract and a private market, typically using the setting of garbage collection and recycling services, and finds that monopoly contracts are more efficient (Dubin and Navarro 1988, Edwards and Stevens 1978).[43] These monopoly contracts allow for production at a larger scale, so this result suggests that economies of scale are likely to be present in these contexts. Later research investigates intergovernmental service delivery, in which economies of scale may be achieved by combining service provision across multiple municipalities (Zafra-Gómez et al. 2013, Warner 2011). Bish and Warren (1972) point out that one issue with intergovernmental service delivery is that it may be less responsive to diverse preferences than municipal provision, presumably since dissatisfied individuals will not be able to "vote with their feet."[44]

Like previous research, the present paper is concerned with the effect of contracting arrangements on economies of scale in government service delivery. Although prior research does explore economies of scale, it does not explicitly

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[43] These papers attribute the cost savings to both economies of scale and economies of density. Economies of density are present in garbage collection because it takes fewer stops and less time for a truck to collect all the garbage from one block compared to half of the garbage from two blocks. Jensen and Stonecash (2005) provide an overview of additional industries studied, such as transportation, maintenance of equipment, fire protection, prison management, and road maintenance.

[44] Voting with one's feet is a reference to Tiebout's argument that local government provision of public goods can be relatively efficient because individuals will choose their most-preferred mix of goods if they are mobile (1956). In later work, Warner and Hefetz (2002) explain that voters are still able to debate the appropriate manner of service provision in intergovernmental cooperation schemes, and may use that debate to satisfy diverse preferences. This avoids the segregation that is the result of "voting with your feet."

investigate how changing the size of the monopoly territory affects costs. The present research can inform larger municipalities, states, and federal government agencies that have the ability to manipulate the size of the monopoly territory.

3.3.2 Contracting changes to increase efficiency

Many papers look at factors that improve contracting success. These include ensuring there is sufficient competition in the bidding process; limiting the principal-agent problem through contract specifications, monitoring and enforcing compliance with contract terms, and employing knowledgeable personnel to oversee the process; developing strong relationships between government and contractors; increasing political support for contracting; building contractor capacity; and limiting implementation complexity.[45]

The aspect of this previous research that most relates to this current paper is the complexity of contract implementation. Theoretically, having fewer and larger contracts can reduce complexity by reducing transaction costs. Previous research has looked at the extent to which potential cost savings are limited by transaction costs such as the cost of monitoring compliance (Nelson 1997) and the extent to which overall contracting performance is decreased by the number of subcontractors (Fernandez 2007). To my knowledge, researchers have not examined how the number of contracts affects

[45] For an overview of the specific research on each of these factors, see Jensen and Stonecash (2005) as well as Fernandez (2007).

production efficiency. Presumably, the gap exists because local contracts, the context of much of the research, tend to be handled as one large contract rather than many small contracts. The present paper examines changes to the number of contracts within a geographic region over time, informing the literature relating contracting complexity to costs.

3.3.3 Production efficiency in the nonprofit context

In the context of for-profit firms, the relationship between firm size and production efficiency is well-documented. In addition to having more market power and economies of scale in production, the largest for-profit firms tend to be the more efficient because of selection. In the for-profit context, Jovanovic (1982) argued that efficient small firms grow and survive and inefficient small firms either fail to grow or exit the industry entirely.

It is unclear if similar forces exist in the nonprofit sector. Scholars have observed that overhead rates, measured as the proportion of expenditures spent on administration and fundraising, are correlated with the size of the nonprofit organization, as measured by revenues (Wise 1997, Lecy and Searing 2015). In the U.S. context, this relationship takes on an inverse U-shaped relationship, with overhead rates growing initially as small, volunteer-run nonprofits professionalize their operations and declining after a sufficient scale is achieved (Lecy and Searing 2015).[46] In the U.K., the top 500 charities experience economies of scale in their overhead costs, administrative costs, and the cost to raise a dollar (Hyndman and McKillop 1999). Interestingly, there is some indication that the largest 500 charities in the U.K. do not seem to experience economies of scale in direct mail, telephone, or in-person fundraising (Sargeant and Kähler 1999), and economies of scale in cost to raise a dollar may disappear after the organization reaches $4M in income (Hyndman and McKillop 1999).[47]

Clearly, economies of scale in overhead costs are only one aspect of production efficiency in nonprofit organizations—the most important aspects of nonprofit operations are pubic goods and social services. Measuring this type of output is challenging, however, and this problem has resulted in a paucity of research on this important dimension of efficiency (Hyndman and McKillop 1999). The present paper contributes to the literature on efficacy in nonprofit service production, because, in the CFC, donation opportunities are actually the service produced. Findings about economies of scale in the CFC provide information about production efficiency for other nonprofits that provide donation opportunities, like the United Way. The present paper also contributes to the larger literature on economies of scale in overhead costs, especially for charities that

[46] In addition, Yi (2010) found that fundraising efficiency, measured using a stochastic production frontier method, rises as nonprofit asset size increases.
[47] These two statistics might be reconciled if one considers that larger charities might choose a different mix of fundraising activities or if particular, efficient subsectors are more likely to include organizations with very large revenues.

organize volunteer led fundraising drives as part of their overhead costs.

3.4 Institutional Context

The Combined Federal Campaign (CFC) is the largest workplace giving campaign in the nation, raising more than $250 million annually from federal government employees. The structure of the CFC is tiered, with one national and many local divisions, each of which corresponds to a fundraising campaign for employees within a geographic boundary. While the Office of Personnel Management (OPM), a federal government agency, oversees the campaign nationally, a local nonprofit administers the campaign within a specific contract service area. The administering nonprofit is known as the Principal Combined Fund Organization (PFCO). The PFCO is hired and directed by a board of volunteers, the Local Federal Coordinating Committee (LFCC), who are employees of the federal government in the local administrative zone. The LFCCs of adjacent zones, in consolidation with their respective PFCOs, make all consolidation decisions.

The CFC provides a fruitful context to look at the effect of nonprofit intermediaries serving more clients over a larger geographic area. First, CFC service areas have increased in geographic scope over time. In 2004, there were 313 service areas; by 2013, there were 163. The consolidation over this time period is the result of encouragement by the OPM, which issued a series of memos (beginning in 2001) explaining how service areas could consolidate and consolidation's benefits.[48] Furthermore, in CFC Regulations 5 CFR § 950.103(a), it states that "… There is no prerequisite regarding the Federal employee population needed to establish or maintain a CFC. However, rather than establishing or maintaining small campaigns, OPM encourages mergers and expansions of mergers of campaigns to promote efficiency and economy."

The OPM memos seem to be responding to rising costs of the CFC overall. CFC costs were highlighted in the report of the 2012 CFC-50 Commission.[49] In addition, the OPM Merger Guidelines highlights cost considerations in its discussion of merger activity. The first reason for a merger discussed in the document is, "Desire to lower high administrative costs – campaign expenses are in excess of 15% of total campaign receipts" (p. 1). Finally, the OPM has justified the 2017 restructuring of the CFC on cost-related grounds, with OPM Director Katherine Archuleta stating "[Employees] wanted lower overhead costs. They wanted more of their money to go directly to the charities they support" (2016).

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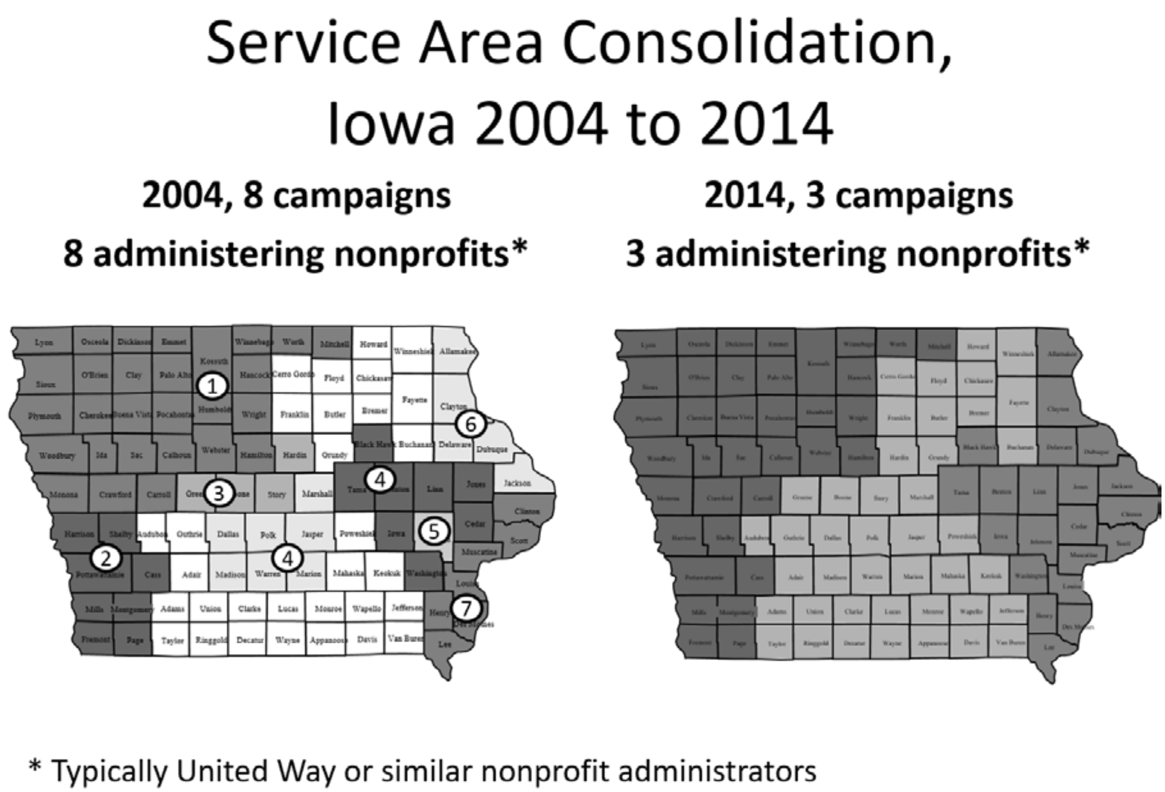
[48] CFC Memorandum 2001-09 states that "The Office of CFC Operations continues to promote mergers whenever appropriate and expects that there is potential, especially among smaller campaigns, to centralize certain functions. This can save on the costs of operating a campaign, thus making the campaign more efficient and yielding greater contributions to participating charities."
The OPM Merger Guidelines document states that "Local campaigns should regularly identify opportunities for partnerships and campaign mergers. In doing so, members of the LFCCs and PCFOs should critically assess the ability of their campaign to offer a cost-efficient campaign and develop an understanding of the opportunities for reducing costs by aligning with other campaigns in the state or region" (p.2).
[49] A figure in the report shows that the cost of the CFC approximately doubled between 1996 and 2010. This included a substantial increase of 50% between 2002 and 2008 (CFC-50 Commission 2012). It is unclear from the report if these numbers are inflation-adjusted.

A second reason that the CFC is a context to examine this research question is because the regulated nature of the CFC provides a degree of standardization to the various offices, which simplifies the consolidation analysis. Federal rules regulate aspects of the campaign such as the organization of volunteer committees, the information provided to donors, the time period for solicitation, and the participation of local (and national) charities.[50] The fact that the context is governed by federal rules reduces the number of variables changing over time, and specifically reduces the changes that might occur simultaneously with the consolidation and complicate the analysis.

3.4.1 Patterns of CFC consolidation

The CFC experienced a relatively steady period of consolidation between 2005 and 2013. Two forms of consolidation occurred, and each form can be observed from changes to the Iowa CFC zone boundaries. The Iowa CFC zone boundaries for 2004 and 2013 are shown in Figure 13. Iowa is a useful illustration of the two forms of consolidation in the CFC.

[50] CFC regulations are found in Title 5, Part 950 of the Code of Federal Regulations. One aspect which had not been standardized during this time was the use of online giving options. I check the robustness of my results to including online giving options as a control.



Source: Campaign maps from national Combined Federal Campaign office.

Figure 13: CFC Geographic Zones

The changes to the CFC in western Iowa were relatively straightforward. In 2008, the Siouxland Area CFC (labeled 1 on map) consolidated into the Heart of the Midlands CFC (labeled 2 on map). I consider this to be a standard consolidation, since two or more administrative zones consolidated without changing the boundaries or the employees served. The changes to the CFC in eastern Iowa took place in several steps. In 2008, the IlIowa Bi-State CFC (7) consolidated the Dubuqueland (6) into its boundaries. Then, in

2009, the IlIowa Bi-State CFC merged the East Central Iowa CFC (4) and the Johnson County CFC (5) into its boundaries. I consider this to be two standard consolidations.[51]

The central Iowa changes are different, and include a second type of consolidation, which I term a non-standard consolidation. First, in 2009, the Ames area CFC (4) merges into the CFC of East Central Iowa (3) to form the Central Iowa CFC. The 2009 change is a standard consolidation. Then, in 2010, the Central Iowa CFC merges into the Northern Lights CFC (not numbered on 2004 map because it is administered out of Minnesota). During this process, the Northern Lights CFC also adds the remaining counties in Iowa.[52] I consider this to be a non-standard consolidation, because changing the boundaries means that the final group of employees in the zone will not be the sum of employees in the two original zones. I exclude consolidations of this type from most analyses, because I cannot discern if changes in outcomes are due to the consolidation or due to the newly-included employees.

Table 33 lists the 121 consolidation events that occurred between 2005 and 2013 in the entire United States. I use a star in this table to indicate that the consolidation was accompanied by some other change to the boundaries of the service area, and is therefore non-standard. There are 25 non-standard consolidations, leaving 96 standard consolidation

[51] Technically, the second consolidation was non-standard, because the campaign also added Adams, Brown, Hancock, Henderson, McDonough, Schuyler, and Warren Counties, IL to its boundaries. However, that is not observable from this map and so is glossed over here.

[52] Some Iowa counties are added to the Northern Lights CFC in 2009 and some are added in 2010. However, this is not critical to the description.

events in most analyses. The number of standard consolidations and other types of changes to zone boundaries in each year is displayed in Table 34. The second row shows the number of zones with standard consolidations in each year. As described previously, standard consolidations are those where two or more administrative zones were combined without changing the boundaries or the employees served. The average number of standard consolidations per year was 23. As shown in the table, there was a notable uptick in consolidations following the 2005 campaign and the 2012 campaign. The third row of Table 34 shows the number of zones that experience non-standard consolidations or other changes to the campaign's boundaries. Changes to boundaries were typically made by adding counties that were previously not covered by any zone or by transferring counties to other zones. Because the number of counties that are not covered by any zone has decreased, the number of these types of changes waned in recent years. Finally, the last row of Table 34 shows that most zones did not change boundaries between years.

Table 33. List of CFC Consolidations, 2009-2013

Year	State	Code	Description
2013	CA	95	Central California CFC merges the Indian Wells Valley CFC (0092) into its boundaries.
2013	CA	105	The SoCal CFC merges the Coachella Valley & 29 Palms Area CFC (0100) into its campaign boundaries.
2013	CO	141	The Metro Denver CFC merges the Larimer County CFC (0142) and Weld County CFC (0145) into its boundaries. The new campaign name is the Rocky Mountain CFC.
2013	FL	192	The Central Florida CFC merges the Space Coast CFC (0181) into its campaign boundaries.
2013	MD	405	The Chesapeake Bay Area CFC merges the Delaware CFC (0175) and the Western Maryland CFC (0407) into its campaign boundaries.
2013	MA	432	The Western Masschusetts CFC merges the Greater Hartford CFC (0162) and Nutmeg CFC (0164) into its campaign boundaries. The new name is the CFC of Connecticut and Western Massachusetts.
2013	MI	457	The Kalamazoo Area CFC merges the Calhoun County CFC (0451) into its campaign boundaries. The new campaign name is the Calhoun and Kalamazoo County CFC.
2013	MO	528	The Gateway CFC merges the Paducah-McCracken Counties CFC (0356) into its campaign boundaries.
2013	NH	571	The Northern New England CFC merges the Capital Region CFC (0620) into its campaign boundaries.
2013	NM	606	Central & Northern New Mexico CFC merges the Southeast New Mexico CFC (0605), the San Juan County CFC (0615), and the Sun Country CFC (0840) into its campaign boundaries. The new campaign name is the Desert Southwest CFC.
2013	NY	638	The North Country CFC merges the Central New York CFC (0634) into its campaign boundaries. The new campaign name is the Central and Northern New York CFC.
2013	NY	639	The Hudson Valley CFC merges the Taconic Valley (0644) CFC into its campaign boundaries.
2013	OH	684	North Coast CFC merges the Greater Northwest Ohio CFC (693) into its campaign boundaries.
2013	OR	728	The Pacific Northwest CFC merges the Coos/Curry/Douglas Counties CFC (0729) into its campaign boundaries.
2013	PA	751	The Southeastern Pennsylvania & Lehigh Valley CFC merges the South Jersey CFC (0580) and the Northeast Pennsylvania CFC (0760) into its campaign boundaries. The new campaign name is the CFC of Eastern Pennsylvania and South Jersey.
2012	AR	72	CFC of Greater Arkansas merges the Jefferson County CFC (0073) into its campaign boundaries.

Year	State	Code	Description
2012	CA	96	The Greater Los Angeles CFC merges the SoCal Tri-County CFC (0109) into its campaign boundaries. It changes its name to the CFC of Greater SoCal.
2012	CA	106	CFC Norcal merges the Central Valley/Sierra CFC (0107) into its campaign boundaries.
2012	FL	185	The Northeast Florida-Southeast Georgia Regional CFC merges the Big Bend CFC (0196) into its campaign boundaries.
2012	IL	249	The Chicago Area CFC merges the East Central Illinois CFC (0248) and the Lake County Illinois CFC (0255) into its campaign boundaries.
2012	LA	371	The Fort Polk - Central Louisiana CFC merges the CFC of Acadiana (0376) into its campaign boundaries.
2012	MS	500	* The Greater Mississippi CFC merges the Northeast MS CFC (0501) into its campaign boundaries. It transfers Scott County to the Jackson Metropolitan Area CFC (0503). It adds Itawamba, Noxubee, Jasper, Winston, and Smith Counties to its campaign boundaries. The campaign name changed to the Greater Mississippi CFC.
2012	NY	621	The Niagara Frontier CFC merges the Greater Rochester CFC (0630) into its campaign boundaries.
2012	OH	682	The Ohio River Valley CFC merges the Central Kentucky CFC (0354) into its campaign boundaries.
2012	PA	754	The 3 Rivers/PA West CFC merges the Laurel Highlands (0742) CFC into its campaign boundaries.
2012	SC	772	The Coastal Carolinas CFC merges the Lowcountry CFC (0771) into its campaign boundaries.
2011	AL		Heart of Alabama CFC merges the Wiregrass CFC (0003) into its campaign boundaries
2011	CT	164	CFC of Southeastern Connecticut merges the Western Central Connecticut CFC (0163) into its boundaries. The new campaign name is the Nutmeg CFC.
2011	FL	185	Northeast Florida-Southeast Georgia CFC merges the North Florida CFC (0184) into its campaign area
2011	NY	631	Greater Rome Area CFC merges the Greater Utica and Herkimer Counties CFC (0637) into its campaign area
2011	NC	655	* Greater North Carolina area CFC merges the Central Carolinas CFC (0652) into its campaign boundaries. It also adds 18 counties.
2011	NC	656	Southeastern North Carolina CFC merges the Cape Fear Area CFC (0661) into its campaign area
2011	PA	751	Southeastern Pennsylvania and Lehigh Valley Area CFC merges the Lancaster County CFC (0747) into its campaign boundaries

Year	State	Code	Description
2011	PA	760	* Luzerne/Columbia Counties CFC merges the Northeast Pennsylvania CFC (0757) into its campaign boundaries. It adds Bradford and Sullivan Counties and changes its name to the Northeast Pennsylvania CFC.
2011	TX	830	* West Central Texas CFC merges the Lubbock Area CFC into its campaign boundaries. It also adds Ector, Garza, and Midland Counties. The new campaign name is Greater West Texas CFC.
2011	TX	840	* Sun Country CFC merges the Val Verde County CFC (0855) into its campaign boundaries. It also adds 10 counties.
2011	UT	870	* Intermountain CFC merges the Southwestern Idaho CFC (0230) and the Southwest Colorado CFC (0147) into its campaign boundaries. It also adds Dolores and San Juan Counties in Colorado.
2010	CA	95	Fresno-Madera CFC merges the Kern, Inyo and Mono Counties CFC (0090) into its campaign boundaries. The new campaign name is Central California CFC.
2010	CA	106	CFC Norcal merges the Yuba-Sutter-Beale CFC (0098) into its campaign boundaries
2010	CA	109	Orange-San Bernardino Counties CFC merges the Mojave Valley CFC (0091) and the Western Riverside CFC (0102) into its campaign boundaries. The new campaign name is So Cal Tri-County CFC.
2010	IN	283	* Greater Indiana CFC merges the Crane Area CFC (0280) into its campaign boundaries. It also adds Brown, Clay, Dubois, Orange, Owen and Pike Counties.
2010	LA	371	The Fort Polk-Central Louisiana CFC merges the Northeast Louisiana (0377) into its campaign boundaries.
2010	MA	432	Pioneer Valley CFC merges the Berkshire County CFC (0434) into its campaign boundaries. The campaign name is changed to the Western Massachusetts CFC.
2010	MN	481	* Northern Lights CFC merges the Central Iowa CFC (0303) into its campaign boundaries. It also adds 20 counties.
2010	MS	500	Southern Mississippi CFC merges the Lauderdale County CFC (0504) into its campaign boundaries.
2010	MO	524	* Heartland CFC merges the Leavenworth Area CFC (0334) into its campaign boundaries. It also added Hickory County, MO.
2010	MO	528	* Gateway CFC merges the Southern Illinois CFC into its campaign boundaries. It also adds 14 counties.
2010	NV	560	The Southern Nevada CFC merges the Northern Nevada CFC (0561) into its campaign boundaries. The new campaign name is the Nevada CFC.
2010	NC	655	Greater North Carolina Area CFC merges the Piedmont Triad CFC (0658) into its campaign boundaries.
2010	OH	682	Greater Cincinnati Metro Area CFC merges the Boyd-Greenup-Carter-Lawrence Counties CFC (0359) into its boundaries. It changes it name to the Ohio River Valley CFC.
2010	OR	728	* Pacific Northwest CFC merges the Rogue Valley (0726) CFC into its campaign boundaries. It also merges Gray's Harbor and Pacific Coun- ties in Washington (formerly served by the Olympic Peninsula CFC (0932)) into its campaign boundaries.

Year	State	Code	Description
2010	TX	857	CFC of North Texas merges the Jackson County CFC (0705) into its campaign boundaries. The new campaign name is CFC of North Texas and Jackson County, OK.
2009	AL	5	Heart of Alabama CFC merges the West Alabama CFC (0010) into its campaign boundaries.
2009	AR	72	CFC of Greater Arkansas merges the North Arkansas CFC (0076) into its boundaries and changes its name to the North Arkansas CFC
2009	CA	106	* CFC of the Bay Area merges the Sacramento/Northern California (0103) into its boundaries. It also adds Alpine County. The new cam- paign name is CFC Norcal.
2009	CA	109	Orange County CFC merges the San Bernardino CFC (0104) into its boundaries. The new campaign name is the Orange-San Bernardino Counties CFC.
2009	FL	189	Tri-County CFC merges the Treasure Coast CFC (0199) into its boundaries. The new campaign name is the Atlantic CFC.
2009	FL	192	Central Florida CFC merges the Volusia-Flagler-Putnam Counties CFC (0182) into its campaign boundaries.
2009	IA	259	*Illowa Bi-State CFC merges the East Central Iowa CFC (0302) and the Johnson County CFC (0306) into its campaign boundaries. It also adds Adams, Brown, Hancock, Henderson, McDonough, Schuyler, and Warren Counties, IL to its boundaries.
2009	IA	303	CFC of Central Iowa merges the Ames Area CFC (0300) into its campaign boundaries.
2009	MN	481	* Northern Lights CFC merges the Lake Superior CFC (0476) into its boundaries. In addition, the campaign adds 36 counties to its boundaries.
2009	MO	524	* Heartland CFC merges the Ozarks Area CFC (0530) into its boundaries. It also add McDonald and Ozarks Counties in Missouri.
2009	NH	571	New Hampshire and Southern Maine CFC merges the Vermont and Upper Valley CFC (0880) into its campaign boundaries. The new campaign name is the CFC of Northern New England.
2009	NM	606	* Central & Northern New Mexico merges the Eastern Mexico CFC into its campaign boundaries. It also adds Catron, Colfax, De Baca, Guadalupe, Harding, Mora, Quay, Sierra, and Union Counties to its campaign boundaries.
2009	OH	685	Heart of Ohio CFC merges the River Cities CFC (0942) into its campaign boundaries. The new campaign name is Heart of Ohio and Tri-State Area CFC.
2009	OK	715	* Tulsa Area CFC merges the Muskogee Area CFC (0711) into its campaign boundaries and adds Cherokee County.
2009	PA	754	3 Rivers CFC merges the Pennsylvania West CFC (0739) into its campaign boundaries. The new campaign name is 3 Rivers/Pennsylvania West CFC.
2009	TX	853	Greater Temple Area CFC merges the McLennan-Falls Counties CFC (0856) into its boundaries.

Note: Most information on consolidations comes from the OPM's CFC website. This list was checked using maps and summary reports provided by the national CFC staff, and errors were corrected.

Table 34. Summary of Campaign Zone Consolidations

	2004	2005	2006	2007	2008	2009	2010	2011	2012
Number of Zones	313	299	277	260	243	226	209	197	184
Standard Consolidations Following Year	20	31	21	23	20	21	12	21	36
Non-standard Consolidations, Boundary Changes Following Year	17	20	14	23	26	23	19	10	5
Unchanging Following Year	276	248	242	214	197	182	178	166	143

Note: In 2013, 163 zones remain. Standard consolidations are those where two or more zones are combined without changing the employees eligible for the CFC in either zone. Non-standard consolidations are complex consolidations where the new zone includes individuals who were not part of either of the original zones due to simultaneous county additions or subtractions. No data manipulation (combination) of zones that will consolidate in the future has occurred.

As shown in Table 35, the consolidation events involve 170 of the original zones from 2004. By 2013, 58 of the 163 zones that remain had experienced at least one consolidation during the previous 10 years. Among the final zones, 70 had experienced no changes to campaign boundaries during that time period.[53] Table 35 also shows that, due in large part to consolidations, the number of employees in the average CFC zone nearly doubled between 2004 and 2013. During the same time period, the pledges and costs in the average zone also grew, but more slowly. Since pledges grew more slowly than employees, it should not be surprising that the giving per employee dropped substantially during this time period. The decrease is due to substantial decreases in participation. The size of the average pledge grew during this time period, which indicates that participation decreases were concentrated among smaller donors. The costs per employee solicited and cost per dollar raised both grew between 2004 and 2014.

[53] 35 of the final service areas experienced a change to campaign boundaries that was not due to a consolidation. The typical (non-consolidation) change was adding counties that were not previously covered by any CFC service area. This is discussed further in the data section.

Table 35. Summary Statistics for Zone-level Data

	Year	
	2004	2013
Zone Information		
Number Employees Solicited	12,731	24,783
	(30,973)	(40,996)
Giving Information		
Total Zone Pledges (2011 $)	977,431	1,241,991
	(4,026,308)	(4,017,146)
Number Employees Giving	4,135	4,013
	(12,339)	(8,289)
Percent Employees Giving	27.87	16.77
	(12.564)	(10.401)
Per Employee Gift Amount (2011 $)	62.78	48.87
	(34.99)	(34.16)
Average Gift Amount (2011 $)	229.95	295.86
	(78.33)	(108.59)
Cost Information		
Budgeted Costs for Zone (2011 $)	94,442	159,203
	(305,590)	(384,040)
Budgeted Cost Per Employee Solicited (2011 $)	7.56	7.79
	(4.54)	(5.61)
Budgeted Costs Per Dollar Donated Ratio	0.131	0.177
	(0.058)	(0.096)
Consolidation Information		
Number of Zones that Ever Consolidated	170	58
Number of Zones with Constant Boundaries	70	70
Observations	313	163

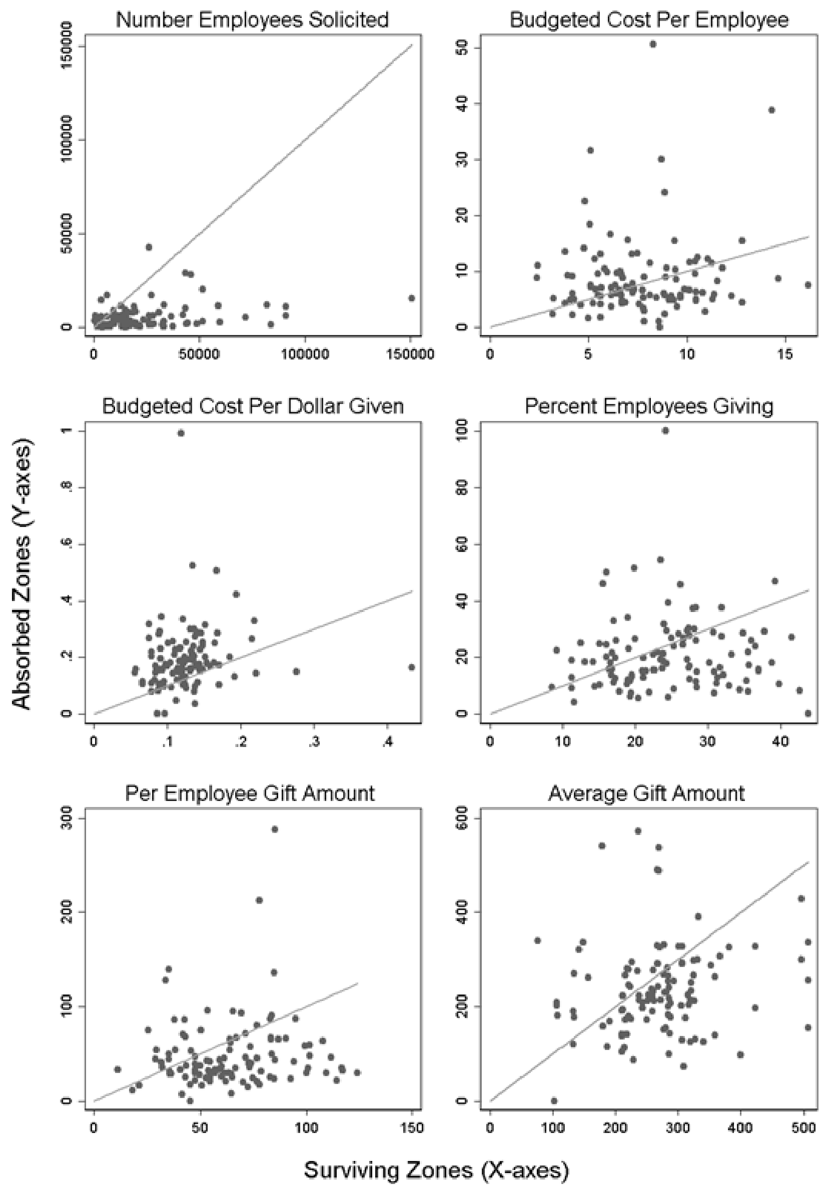
Note: Standard deviations in parentheses. Based on records from CFC. No data manipulation (combination) of zones that will consolidate in the future has occurred.

By analyzing the events in Table 33, patterns of consolidation begin to emerge. Consolidating service areas are always geographically adjacent. Following consolidation, a nonprofit from one of the two original service areas is typically selected to administer the CFC in the new administrative zone.[54] I refer to the zone that administers the campaign following a consolidation as the surviving zone.

Typically, in two-zone consolidations, the surviving zone is larger and more successful than the zone that is absorbed. Figure 14 contains a series of scatter plots comparing the surviving zone (Y-axis) to the zone that is absorbed (X-axis) for two-zone mergers. Each plot compares the two zones on a separate characteristic. Data points above the line indicate zones where the surviving zone performed better on that characteristic, while data points below the line indicate zones where the zone that was absorbed performed better.

As shown in Figure 14, the surviving zone has more employees than the absorbed zone in 90% of cases. The surviving zone has a lower cost per dollar raised ratio in 80% of cases. It has larger average gifts in 69% of cases. Finally, it has a higher participation in 62% of cases. Notably, these statistics indicate that the zone that is absorbed may be performing better than the surviving zone on some metrics. The absorbed zone had higher participation just 38% of the time. The average gift was higher in the absorbed zone just 35% of the time.

[54] Typically, consolidation involved just two service areas, although in 13 cases, consolidation involved three or more service areas. These consolidations are included as multiple pairs for the analyses of consolidating pairs in this section, but are included together in most analyses.



Note: N=96 consolidations across all years; consolidations of more than two zones have more than one data point. Pre-consolidation data used. All dollar amounts in 2011 dollars. Straight line indicates surviving and absorbed zones were equal. No data manipulation (combination) of zones that will consolidate in the future has occurred.

Figure 14: Scatter Plots Comparing Absorbed and Surviving Zones

Other patterns distinguish zones that consolidate during this time period from those that do not consolidate. For the purposes of this comparison, I will refer to these as consolidating and non-consolidating zones. Table 36 compares consolidating and non-consolidating zones along several dimensions using 2004 data.

Initially, consolidating zones tended to be smaller and less successful on average than the non-consolidating zones. In 2004, consolidating zones had 52% fewer employees than non-consolidating zones. Meanwhile, budgets in the consolidating zones were 61% smaller. These two facts meant that the consolidating zones typically spent 13% less per employee than non-consolidating zones, although this difference is not statistically significant. Consolidating zones also tended to raise less money in 2004. On a per-employee basis, they raised 20% less than non-consolidating zones. Since the average gift amount was nearly the same, the difference seems to be because the percent of employees giving is lower by 16% in the consolidating zones. The cost per dollar raised was 14% higher in consolidating zones.

Table 36. Comparison of Zones with Simple Mergers vs. Constant Boundaries

	2004 Means, Zone-level Data		
	Never Consolidate	Consolidate	Difference, T-test
Number Employees Solicited	22,056	10,661	11,395*
Per Employee Gift Amount (2011 dollars)	73.11	58.31	14.80**
Percent Employees Giving	31.65	26.39	5.26**
Average Gift Amount (2011 dollars)	227.72	228.64	-0.92
Budgeted Costs for Zone (2011 dollars)	183,738	71,916	111,821*
Budgeted Cost Per Employee Solicited (2011 dollars)	8.32	7.27	1.05
Budgeted Costs Per Dollar Donated (2011 dollars)	0.119	0.137	-0.017*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. First column is zones with constant boundaries between 2004 and 2013. Second column is zones with at least one simple consolidation. No data manipulation (combination) of zones that will consolidate in the future has occurred.

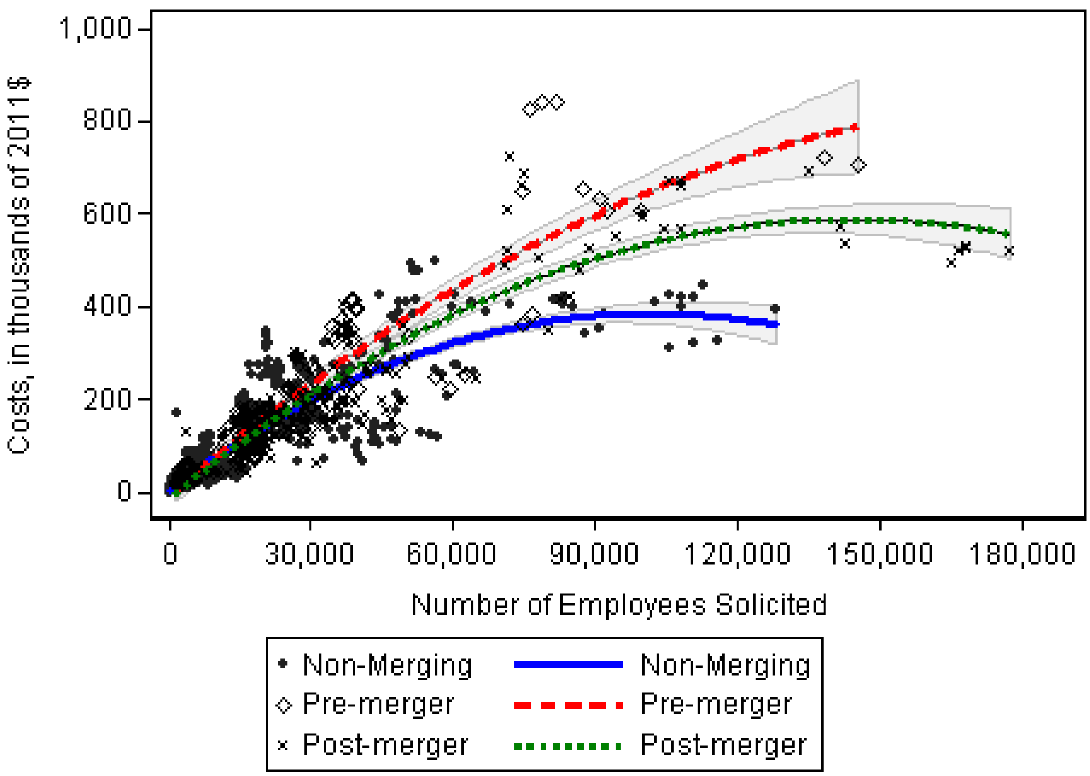
3.4.2 Potential mechanisms affecting consolidation outcomes in the CFC

Consolidation changes two aspects of campaign operations: (i) the management and (ii) the scale of operations, including both the number of employees and the number of nonprofits within the service area. Each of these aspects can affect the production efficiency or the consumption efficiency of the campaign within the service area. The current data cannot separately identify the effects of each mechanism described here, so testing the role of each mechanism is left for future work.

When zones are consolidated, the staff members managing the campaign change for the absorbed zone. On average, one might expect the effect of this change to be positive on production efficiency. The expectation would hold if, generally, a zone with higher production efficiency absorbs a zone with lower production efficiency and management skill positively affects production efficiency. However, the rather restrictive administrative rules guiding the policies and procedures of the CFC might limit the role of managers in service delivery, and therefore might somewhat mute the effect of managerial skills.

Changes in campaign management can also have negative consequences. New managers may not have strong relationships with leadership volunteers, federal employee managers, and nonprofit organizations in the absorbed zone. Limited relationships may mean that managers are not able to tailor programs to local needs and preferences, which may decrease consumption efficiency.

The scale of campaign operations also changes when zones are consolidated. The larger scale means that more employees and nonprofits are covered by each nonprofit administrator. Changing the number of covered employees is likely to have effects on both employee services and services to participating local nonprofit organizations. First, many employee services, such as website setup and newsletters, have a cost structure with large fixed costs and low variable costs. With this cost structure, the average cost per employee is likely to decrease as the number of employees served increases, leading to an increase in production efficiency. Figure 15 is a scatter plot showing the relationship between the cost of administering the CFC within a zone and the number of employees of the zone. The concave fitted lines support the hypothesis that the CFC experiences economies of scale.



Note: All dollar amounts in 2011 dollars. Shaded lines are 95 percent confidence intervals. Only zones with less than 200,000 employees are included. Pre-consolidation costs and employee counts are the the sum of the values for the zones which will consolidate in the future.

Figure 15: Cost Function for the CFC (Showing Economies of Scale)

The other way that scale manifests itself in the CFC is through scale's effect on the services to participating nonprofit organizations. After consolidation, a zone encompasses more nonprofit organizations, which may or may not be beneficial to nonprofit participation. It is unclear what the production function underlying nonprofit participation in the CFC is. Neither the volunteer leadership (LFCC) nor the nonprofit intermediary organization (PCFO) has direct responsibility for recruiting nonprofit organizations to participate, although the PCFO is required to process and organize applications for LFCC review and approval. If nonprofit participation is affected most by mass communication activities, like the zone's website, then the average cost of recruiting should decline and more nonprofits should participate. But if participation is reliant on one-on-one communication, perhaps because many nonprofits have questions about the required forms, then there may be a limit on the number of nonprofits that the staff can assist. Limited relationships between new managers and nonprofits in the absorbed area may also deter participation. If nonprofit participation increases after consolidation, this may have a positive effect on consumption efficiency, as employees may be more pleased with their choices. Conversely, if nonprofit participation decreases, this may have a negative effect on consumption efficiency, as employees may not be able to access the nonprofit options that they had prior to consolidation. Table 37 shows that nonprofit participation typically decreases after consolidation. The first two columns show average year-over-year differences in the number of participating nonprofits, with the first column showing the zones that consolidate in that time period. The final summary row shows that, on average, consolidating zones lose 0.06 local organizations while non-consolidating zones typically gain 0.04 local organizations in each year. The third column shows the difference is statistically significant.

Table 37. Comparison of Nonprofit Participation in the CFC, Year-over-year differences for Consolidating and Non-consolidating Zones

	Means		
	Consolidating	Not Consolidating	Difference, T-test
Change in Nonprofit Count, 2008 to 2009	-0.67	-0.30	-0.37
Change in Nonprofit Count, 2009 to 2010	0.16	0.34	-0.18
Change in Nonprofit Count, 2010 to 2011	-0.00	0.02	-0.02
Change in Nonprofit Count, 2011 to 2012	-0.08	0.03	-0.11
Change in Nonprofit Count, 2012 to 2013	-0.04	0.01	-0.05*
Change in Nonprofit Count, All Years	-0.06	0.04	-0.10*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. First column includes zones that have simple consolidations from 2009 to 2013. Second column includes zones with no consolidations and zones with simple consolidations that occur in other years. Only zone-years that are part of the final analysis sample are included here. Only local organizations are included. If a single nonprofit appears in both zones pre-consolidation, it is only counted once to avoid artificially inflating the pre-consolidation count.

The combined effect of all these changes is complex. However, given that zones choose to consolidate, the employee volunteers in the two LFCCs who are making the decision must believe that the effect is positive on some dimension.[55] The decisionmakers would not choose to consolidate if they expected both employee satisfaction with the campaign to decrease and the cost of the campaign per employee to increase. If the decisionmakers are rational and well-informed, then one should hypothesize a positive overall effect of consolidation

3.5 Data

The national office of the CFC/OPM has provided aggregate data at the level of the local administrative zone from 2003 to 2013 for this work. The data include total dollars donated in the zone, information on number of donors and employees solicited, and a measure of campaign costs.

I use the data to test whether consolidation of service areas affects production efficiency, consumption efficiency, and overall efficiency in the context of the CFC. Production efficiency is measured using cost per employee. Cost per employee is a good measure of production efficiency because the service being provided is the opportunity to donate.[56] The cost variable used is the budgeted costs reported by the CFC on the year-

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[55] In fact, OPM Merger Guidelines state, "A merger has to be a win/win for everyone. All parties should analyze what is in the best interest of the federal employee" (p. 2).

[56] Cost per unit of output (or average cost) is arguably the most common measure of production efficiency used in the literature. For instance, when evaluating contracts for sanitation services, the measure used is collection price per

end summary report. Since budgeted costs are not final, this measure may introduce some measurement error. Measurement error in the dependent variable does not bias the results of OLS, but does make estimation less precise and, therefore, increases standard errors.

To explore the relationship between consolidation and consumption efficiency, I examine three outcomes. The first is dollars pledged per employee. Dollars pledged per employee is calculated by taking the total amount donated in the service area and dividing it by the number of employees served. Dollars pledged per employee is not a direct measure of consumption efficiency. Directly measuring consumption efficiency would entail asking employees about their satisfaction with various aspects of campaign operations, especially the mix of charities, the information provided, and the solicitation methods employed. Instead, the indirect measure of dollars pledged per employee is used to measure overall satisfaction of employees with the workplace giving opportunity provided by the CFC. If dollars pledged per employee is falling after controlling for economic conditions and other environmental factors, this is arguably a signal of falling consumption efficiency, because it indicates that employees were happier with an earlier version of the CFC's system or offerings. I also examine the two determinants of dollars pledged per employee: participation rate and dollars pledged per donor. These two measures might capture different aspects of consumption efficiency. The participation

household (Edwards and Stevens 1978), and when evaluating garbage services, the measure used is cost per yard of garbage collected (Dubin and Navarro 1988).

rate might capture satisfaction with the solicitation process, while dollars pledged per donor might capture satisfaction with the selection of local nonprofit organizations participating in service area. Encouraging participation by local organizations may be a form of customizing the campaign to local preferences. To test if local participation is driving consumption efficiency, I use data on the local giving in each zone to create an additional outcome, local dollars pledged per employee, for some analyses.

To understand the combined effect of changes to production efficiency and changes to consumption efficiency, I examine overall efficiency. I measure overall efficiency using cost per dollar raised. Cost per dollar raised is a common efficiency measure in the fundraising profession (BoardSource 2017), and it also has the benefit of being the quotient of my other primary measures of interest.[57] Since the primary purpose of the CFC is to raise funds, using a measure of fundraising efficiency seems to be an appropriate way to describe the overall efficiency of the work.

$$Cost\ per\ Dollar\ Raised = \frac{Cost\ per\ Employee}{Dollars\ Pledged\ per\ Employee}$$

The treatment I am interested in is standard consolidation of zones in the CFC. Because most of my control variables are only available from 2008 onwards, I define a

[57] Another common measure of fundraising efficiency is the fundraising return on investment (Aldrich 2009, Ritchie and Kolodinsky 2003, Sargeant and Kähler 1999), which, in the case of the CFC, would be the dollars pledged per employee divided by the cost per employee. This is the mathematical inverse of the measure chosen here, and would not affect the results. Alternatively, many measures of nonprofit performance examine the overhead cost ratio. The overhead cost ratio is not applicable in the context of the CFC, because there are no non-fundraising program costs, and so the numerator and the denominator will always be equal.

service area as treated if the zone experiences a consolidation from 2009 onwards. Using the 2009 cutoff means that I always have one year of pre-treatment characteristics, including controls. When a service area undergoes multiple consolidations post-2009, I consider the year of first consolidation to be the treatment year.

In addition to the data provided by the CFC, I have collected data on federal workforce and economic conditions, which I will use as control variables. Using the campaign maps provided by the CFC, I identify the specific states and counties covered by each zone in each year. I match this geographic information with county-level and state-level data sources to create zone-specific, time-varying controls for 2008 to 2013.

I include three types of control variables: variables related to the characteristics of federal workers in the zone, variables related to local economic conditions, and variables related to zone characteristics. Federal workforce data comes from three sources.[58] The primary source is the Office of Personnel Management, which releases individual-level statistics on federal civilian employees each year. I select the following characteristics to include as controls: mean length of service, mean age, mean salary, proportion with a professional occupation type, proportion with an administrative occupation type, proportion female, and proportion permanent. I also use Congressional Research Service

[58] OPM data is recorded at the individual worker level, but location of the worker is identified by State, rather than by county. When a zone is only in one state, I assign the zone the state-level means for each variable. When a zone spans more than one state, I first count the zone's counties in each state and then assign the zone the county-weighted average of the two state-level means.

data on the size of the postal workforce[59] and Department of Defense reports on the size of the military at the state level over time. The counts by state-year from these three data sources allow for the estimation of percent postal employees and percent military employees by state and year.

Each of these personnel-related control variables is supported by prior research. Research on workplace giving, as well as non-workplace giving, has found that income (Osili et al. 2011, Christensen et al. 2012) and years employed at the workplace (Nesbit et al. 2012, Christensen et al. 2012) affect donation amount. Some previous work finds that women are more likely to give in the workplace, while other work does not find an effect of gender (Leslie et al. 2013, Osili et al. 2011). The effect of age is also mixed in previous research, but is sometimes significant (Osili et al. 2011, Christensen et al. 2012). Education has also been found to affect workplace giving (Osili et al. 2011). While I do not observe education in my data, I do include occupation type (with blue collar omitted) to proxy for level of education. Position in the workplace has been found to be a predictor of giving in other workplace contexts, such as a university (Christensen et al. 2012). Attachment and identification between the employee and the workplace has also been shown to be a driver of workplace giving (Nesbit et al. 2012), a concept I operationalize with permanent employment status. Finally, Shaker et al. (2014) document the

[59] Reports are available for each year, although the date of the data varies somewhat (2009 data is from March 2010, for example). Only career employees are included in the 2009 and 2010 data. For these two year, I estimate the total postal employees under the assumption that the proportion of career to non-career employees is same across states.

importance of workplace culture on giving to workplace campaigns. It can be argued that the executive branch, the military, and the postal service tend to have distinct cultures, but they cannot be analyzed separately with this data. Instead, I control for changes to the proportion of employees from each of these groups.

The model also includes two measures of local economic conditions in the control variables: unemployment and per-capita income. I use unemployment data from the Bureau of Labor Statistics. To construct the zone-level unemployment rate, I divide the total civilian unemployment in the within-zone counties by the total civilian labor force in the counties. I use per capita personal income data from the Bureau of Economic Analysis to measure income.[60] Local economic conditions can affect workplace giving in two ways: through the economic situation of a spouse who is not a federal employee and through changing perceived charitable need in the local community. When per-capita income and unemployment in a local area change, it changes the probability that the spouse of a federal worker is unemployed or underemployed. Previous research shows that income and employment status are linked to charitable giving (Havens et al. 2006, Toppe et al. 2002). Research also documents that awareness of need in the local community is an important driver of giving (see Bekkers and Wiepking (2011) for a review).

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[60] These data are recorded at the county level. I assign the zone the mean value of the counties within the zone's service area.

Finally, I construct a variable to capture the proportion of a service area that is offering employees the option to give online. I use data from the two main software providers for online CFC giving to observe the zones using online donations in each year. Although it is possible that some zones may use other means to offer online giving, OPM reports that these software systems account for the vast majority of online giving. It is necessary to include an indicator for online giving as a control because consolidation and changes to online giving are correlated. During this time period, when a zone offering online giving consolidated with a zone that did not offer online giving, the system was expanded to include the new employees. To avoid misattributing changes due to online giving options to consolidation, known as omitted variable bias, the availability of online giving must be included as a control.

3.5.1 Constructing the analysis sample

The goal of the analysis is to understand how consolidation affects campaign results. Campaign results need to be easily comparable before and after consolidation. While the results after consolidation are naturally contained on one zone's record, the results prior to consolidation span two or more zones' records. Combining these two or more zones' records into one data point per year of the panel is necessary for a proper comparison. The process of combining records over a long panel is complicated by the fact that zones experience changes other than standard consolidations. When zones experience non-standard consolidations, in which counties are added or subtracted from the service area, the pre-consolidation and post-consolidation results are no longer comparable because different employees and offices are covered. Therefore, these zones must be excluded from the analysis.

I construct the combined-record analysis sample in three steps. First, I limit the data to all zones that existed in 2013 and experienced at least one standard consolidation. I assign each of these zones a unique identifier. Second, I work backward over time and assign that same identifier to the group of zones that consolidated to form the 2013 zone. Third, if counties are added or subtracted from the zone, I code all previous years for that zone as missing. By coding the zone as missing, I eliminate years where a zone's boundaries are not comparable to the final boundaries.

The final analysis sample contains one record per year for each geographic zone that will eventually consolidate. The record encompasses the same set of counties, and therefore the same federal workers, for all years.[61] By holding the counties and workers constant before and after the consolidation, the analysis can also hold unobservable factors specific to the geographic region or employees constant, as long as those factors do not vary over time.

3.5.2 Descriptive statistics for the analysis sample

Table 38 contains descriptive statistics for the analysis sample. The sample

[61] Technically, the same positions are covered by the final analysis sample. There is no guarantee that the same workers are employed in each position in each year. The average length of service for federal workers during this time period is 13 years, so many but not all of the workers will be constant in these zones.

contains 45 geographic service areas with at least one standard consolidation. The panel contains 26 service areas with full 10-year panels, and many shorter panels due to service areas having changes and complex consolidations. The average panel length is 8.3 years. Table 38 includes covariate means and standard deviations for the analysis sample, as well as minimum and maximum values.[62] Most of the service areas experience only one standard consolidation within the years covered by the analysis sample. However, 13 experience two standard consolidations, 4 experience three consolidations, and 2 experience four consolidations.

[62] The control variables have fewer observations (250 rather than 375) because they are only included for 2008 to 2013 at this time.

Table 38. Summary Statistics on Consolidated Data

	Consolidated Data				
	N	Mean	Std Dev	Min	Max
Total Pledges ($)	375	1,708,682	(1,716,409)	54,951	7,739,507
Per Employee Gift Amount ($)	375	57.79	(22.81)	8.02	169.00
Proportion Employees Giving	375	0.226	(0.081)	0.030	0.559
Average Gift Amount ($)	375	263.81	(70.46)	99.10	530.87
Budgeted Costs ($)	375	194,940	(168,477)	12,860	844,012
Budgeted Cost Per Dollar Given	375	0.138	(0.066)	0.050	1.037
Budgeted Cost Per Employee	375	7.45	(3.49)	2.05	37.36
Number Employees Solicited	375	30,253	(30,433)	1,163	177,341
Offers Online Giving	250	0.382	(0.436)	0.000	1.000
Per Capita Personal Income ($)	250	36,628	(5,311)	27,453	51,698
Unemployment Rate	250	0.083	(0.022)	0.036	0.159
Average Length of Service	250	12.92	(0.98)	10.24	15.87
Average Age	250	45.83	(0.68)	43.81	47.44
Average Salary ($)	250	70,634	(6,253)	57,085	91,766
Proportion Female	250	0.436	(0.039)	0.286	0.514
Proportion Permanent Status	250	0.874	(0.034)	0.745	0.937
Proportion Professional Category	250	0.249	(0.034)	0.179	0.356
Proportion Administrative Category	250	0.324	(0.051)	0.217	0.449
Proportion Uniformed Military	250	0.221	(0.176)	0.000	0.655
Proportion Postal Service	250	0.195	(0.125)	0.000	0.487

Note: All dollar amounts in 2011 dollars. Data has been manipulated so that zones that eventually consolidate are in one record. Control variables available for a smaller panel of years, leading to a lower number of observations for these variables.

3.6 Method of Analysis and Identification

To understand the effects of service area consolidation on fundraising costs and giving, I perform a differences-in-differences analysis. The analysis uses service areas that consolidate in a given year as the treated group. The control group needs to be equivalent but untreated. Choosing the control group carefully will help to ensure that the measured effects are due to merging rather than other unobserved factors.

3.6.1 Choice of control group

Non-consolidating service areas are not a good control group for consolidating service areas. Table 36 showed that consolidating service areas are typically smaller and less successful than non-consolidating areas, as the earlier analysis showed. It is also likely that consolidating service areas are unobservably different than non-consolidating service areas.

A better control group for the service areas that consolidate in any given year is the set of service areas consolidating in other years. Table 39 provides evidence that service areas that consolidate in other years are appropriate controls. Table 39 includes evidence from three years of the panel (other years give similar results). The first column shows the pre-consolidation mean for the zones consolidating in the following year. The second column shows the means for zones that consolidate in other years, which are the control group. The final column shows the difference, and indicates the results of a t-test for differences between means.

Table 39. Covariate Balance - Comparison of Control Groups Over Time

	Zone-level Mean Values		
	Consolidate 2005	Consolidate Other Years	Difference
2004			
Number Employees Solicited	10,608	11,061	-453
Per Employee Gift Amount (2011 dollars)	58.25	58.80	-0.55
Percent Employees Giving	26.44	25.98	0.46
Average Gift Amount (2011 dollars)	228.61	228.91	-0.31
Budgeted Costs for Zone (2011 dollars)	70,385	83,402	-13,017
Budgeted Cost Per Employee Solicited (2011 dollars)	7.19	7.89	-0.71
Budgeted Costs Per Dollar Donated (2011 dollars)	0.135	0.149	-0.014
	Consolidate 2009	Consolidate Other Years	Difference
2008			
Number Employees Solicited	15,989	8,404	7,585
Per Employee Gift Amount (2011 dollars)	58.18	62.50	-4.32
Percent Employees Giving	24.20	26.82	-2.62
Average Gift Amount (2011 dollars)	247.03	237.41	9.62
Budgeted Costs for Zone (2011 dollars)	99,637	81,211	18,425
Budgeted Cost Per Employee Solicited (2011 dollars)	7.62	9.42	-1.81
Budgeted Costs Per Dollar Donated (2011 dollars)	0.143	0.147	-0.004
	Consolidate 2013	Consolidate Other Years	Difference
2012			
Number Employees Solicited	26,920	19,621	7,299
Per Employee Gift Amount (2011 dollars)	49.34	51.51	-2.17
Percent Employees Giving	18.24	17.84	0.40

Average Gift Amount (2011 dollars)	281.18	289.98	-8.80
Budgeted Costs for Zone (2011 dollars)	164,816	109,397	55,419
Budgeted Cost Per Employee Solicited (2011 dollars)	6.64	7.07	-0.43
Budgeted Costs Per Dollar Donated (2011 dollars)	0.143	0.159	-0.016

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Based on zone-level records from CFC. No data manipulation (combination) of zones that will consolidate in the future has occurred. Campaigns are included in this table if and only if they have a simple consolidation in some year.

As shown in the last column of Table 39, there are no significant differences between the zones about to consolidate and those that consolidate in other years. The zones in the control group and the treatment group are relatively similar to each other. Because the two groups are similar, at least on observable characteristics, it increases confidence that the control group zones experience the outcomes that the treatment group zones would have had in the absence of consolidation.

3.6.2 OLS analysis

To understand how CFC outcomes change following service area consolidation, I exploit the within-service area variation induced by consolidations over time. Specifically, I use a difference-in-differences research design that asks whether outcomes change more in service areas that consolidate between 2009 and 2013 than in service areas that consolidated in earlier years.

Formally, I estimate fixed effects ordinary least squares (OLS) panel data models, where I use CFC outcomes (as previously described in the data section) as the dependent variable. The OLS model estimated is shown in equation (1). In the equation, the subscript *z* indicates a value that varies at the zone (service area) level, while the subscript *y* indicates a value that varies by year.

$$\begin{aligned} Outcome_{zy} = \beta_1 + \beta_2 PostConsolidation_{zy} + \beta_3 Capita_{zy} + \beta_4 Capita^2_{zy} + \beta_5 Online_{zy} \\ + \theta_1 Economy_{zy} + \theta_2 Demographics_{zy} + \gamma Zone_z + \delta Year_y + \epsilon_{zy} \end{aligned} \quad (1)$$

In a second model, I add linear time trend variables to the model. The second specification allows for the treatment and control groups have group-specific trends in outcomes over time. Like in the main analysis, the coefficient of interest in this model is β_2.

$$\begin{aligned} Outcome_{zy} = \beta_1 + \beta_2 PostConsolidation_{zy} + \beta_3 Capita_{zy} + \beta_4 Capita^2_{zy} + \beta_5 Online_{zy} \\ + \theta_1 Economy_{zy} + \theta_2 Demographics_{zy} + \lambda_1 TimeTrend_y \\ + \lambda_2 Treated_z \times TimeTrend_y + \gamma Zone_z + \delta Year_y + \epsilon_{zy} \end{aligned} \tag{2}$$

In a final model, I allow the treatment group to follow a different time trend following consolidation. This change increases model flexibility by allowing both an initial and a long-term effect of consolidation. There are two coefficients of interest in this model: β_2, which represents the initial effect of the consolidation on the outcome, and λ_3, which represents the effect of the consolidation on the longer-term trajectory of the outcome.

$$\begin{aligned} Outcome_{zy} = \beta_1 + \beta_2 PostConsolidation_{zy} + \beta_3 Capita_{zy} + \beta_4 Capita^2_{zy} + \beta_5 Online_{zy} \\ + \theta_1 Economy_{zy} + \theta_2 Demographics_{zy} + \lambda_1 TimeTrend_y \\ + \lambda_2 Treated_z \times TimeTrend_y + \lambda_3 PostConsolidation_{zy} \times TimeTrend \\ + \gamma Zone_z + \delta Year_y + \epsilon_{zy} \end{aligned} \tag{2B}$$

3.6.3 Identification

Using service areas that consolidate in other years as a control group relies on consolidation timing being random for identification. Here, anecdotal evidence suggests that the choice to merge may be primarily driven by staff turnover at the intermediary nonprofit administrators and only secondarily related to campaign costs or results (G. Masai-Wood, personal communication, January 2014).

If consolidation is completely random, then there should not be any observed predictors of consolidation timing. In Table 40, I use a logit model to test the correlation between observed zone characteristics and consolidation timing. In the table, I restrict my analysis to the first observed consolidation in each service area. The first column of Table 40 examines the predictors of consolidation. None of the observed covariates is significant. The non-significant results provide support for the proposition that consolidation timing is random. The second column of Table 40 examines the predictors of the first consolidation in 2009 or later, which are the years used in most analyses.[63] The second column shows that zones that offer online giving are less likely to consolidate. The relationship between consolidation and online giving is not surprising, because zones typically extend their online giving systems to any zones that they absorb in a consolidation.[64] Therefore, zones that have already consolidated will have extended online giving, but zones that are yet-to-consolidate will not have done so. The significant coefficient on the online giving variable can be understood as a result of consolidation, not a predictor of consolidation. The second column also supports the proposition that consolidation timing is random.

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[63] In the second column, some service areas that consolidate before 2009 and never consolidate again would be shown as never consolidating. In service areas that consolidate twice, once pre-2009 and once post-2009, the post-2009 consolidation would now be coded as the first.

[64] Likewise, if an absorbed zone had online giving pre-consolidation, the whole zone typically gets online giving capabilities post-consolidation. Consolidation almost never causes a zone to lose online giving options.

Table 40. Predictors of Consolidation in the Following Year

	Consolidated Data	
	First Consolidation	First Consolidation Post-2009
Number Employees Solicited (1000s)	0.0112	0.0164
	(0.00986)	(0.00862)
Proportion Employees Giving	8.682	0.765
	(9.295)	(8.550)
Per Employee Gift Amount ($)	-0.0335	-0.000958
	(0.0452)	(0.0394)
Average Gift Amount ($)	0.00642	-0.00292
	(0.00914)	(0.00828)
Budgeted Cost Per Employee	0.125	0.0581
	(0.193)	(0.171)
Budgeted Cost Per Dollar Given	-4.882	-3.468
	(9.603)	(8.899)
Per Capita Personal Income ($1000s)	0.0526	0.0145
	(0.0614)	(0.0531)
Unemployment Rate	23.78	5.701
	(16.17)	(14.58)
Average Length of Service	-0.443	-0.157
	(0.427)	(0.367)
Average Age	0.389	-0.153
	(0.861)	(0.676)
Average Salary ($1000s)	0.0440	-0.0454
	(0.121)	(0.0937)
Proportion Female	19.88	18.12
	(11.13)	(9.787)
Proportion Permanent Status	-2.553	4.125
	(15.10)	(12.60)
Proportion Professional Category	-28.94	-1.870
	(17.91)	(12.36)
Proportion Administrative Category	2.551	4.810
	(11.63)	(9.797)
Proportion Uniformed Military	-1.728	-0.455
	(2.280)	(1.947)
Proportion Postal Service	-3.679	-1.985
	(2.541)	(2.101)

Offers Online Giving	-1.228	-1.592*
	(0.803)	(0.724)
Observations	250	250
Adjusted R^2		

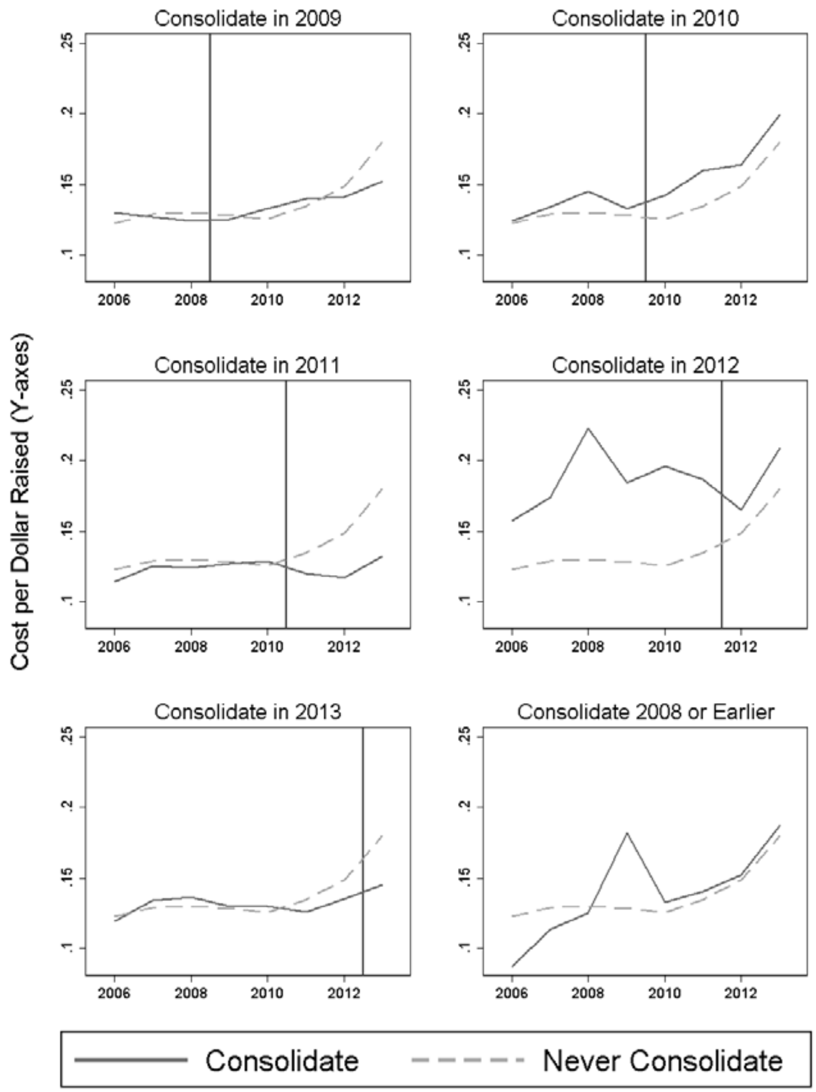
Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Odds ratios reported. Sample is consolidated records from CFC. Campaigns are included in the analysis sample if and only if they have a simple consolidation in some year.

3.7 Consolidation outcomes

I now turn to the main question of whether consolidation influences outcomes in the CFC. I begin with some examples of consolidations and figures based on the raw data. These results do not control for other important factors which may affect CFC outcomes over time. Next, I present the results of the regression analyses that include controls and reflect the identification strategy discussed in Section V.

3.7.1 Examples in the raw data

I start by showing the overall results of consolidation over time using a set of figures. Figure 16 shows the cost per dollar raised over time for consolidating zones and non-consolidating zones, by year of consolidation. For example, the first, upper-left, figure shows the cost per dollar raised for zones that consolidated in 2009, relative to zones that did not consolidate from 2004 to 2013. In these figures, post-consolidation years are to the right of the vertical lines, and pre-consolidation years are to the left of the vertical lines. Post-consolidation gains in cost per dollar raised would be shown by a solid line that decreases and diverges from the dashed line during the post-consolidation years. In most of the figures, immediate post-consolidation gains are not evident. However, the 2011 consolidations appear to have produced both immediate and longer-term efficiency gains. The 2012 consolidations may also fit this pattern, although there is substantial noise in the analysis for this year, due to a small number of 2012 consolidations.



Note: Vertical lines represent consolidation years noted in the figure titles. Dashed lines represent zones that do not consolidation between 2004 and 2013. Consolidation year was defined as the first consolidation post-2009. If there were 2 consolidations post-2009, data from after the second consolidation was dropped. If there was a consolidation between 2006 and 2009, data before the pre-existing consolidation was dropped.

Figure 16: CFC Cost Per Dollar Donated Over Time, by Year of Consolidation (and Comparison with Service Areas That Never Consolidate)

The inconsistent consolidation outcomes documented in these figures can also be observed by examining specific examples of consolidation. One successful consolidation example is the 2012 consolidation of the Lowcountry CFC into the Coastal Carolinas CFC in South Carolina. Prior to consolidation, the Lowcountry CFC was spending $54 thousand dollars per year to raise $188 thousand dollars. They were spending approximately 28 cents to raise a dollar. The participation in the CFC was good, at 24%, but most gifts were small, on average $72. This meant that pledges per employee totaled only $17.40 The Coastal Carolinas CFC was much more successful. They spent $221 thousand dollars and raised $1.5 million, with a cost per dollar raised of $0.15. The campaign's participation rate was similar to the Lowcountry rate, at 25%, but the average gift in the campaign was larger, at $308. After consolidation, the new Coastal Carolinas campaign spent $258 thousand dollars and raised $1.78 million. As a result, the cost per dollar raised fell to $0.14, which was especially impressive because the national cost per dollar raised actually increased in 2012.

However, not all consolidations led to these overwhelmingly positive results. In 2013, the Gateway CFC absorbed the Paducah-McCracken Counties CFC, which was much smaller. Prior to the merger, the Paducah-McCracken CFC had a cost per dollar raised of $0.07. They raised a bit less than $100,000, but spent only about $7400 per year. The participation rate was excellent, at 54%, and employees tended to give large gifts, with an average gift size of $390. The Gateway CFC was also very successful, and much larger. The campaign raised approximately $2.9M per year and spent around $224 thousand, with a cost per dollar raised of $0.08. In the Gateway CFC, 23% of employees gave, with an average gift size of $332. Unfortunately, 2013 was not a good year for the newly consolidated campaign. Cost per dollar raised actually increased to $0.10, largely because participation fell to 18%. This result is disappointing, but the raw data do not reveal if the result is due to the consolidation or to overall problems with CFC performance in 2013. To separate these factors, I next conduct regression analyses that account for additional factors such as time trends and nationwide CFC performance in each year.

3.7.2 OLS outcomes

The results from the basic differences-in-differences OLS analysis in Table 41 are surprising. Most of the coefficient values cannot be statistically distinguished from zero, and many of the coefficients are the opposite sign of what was predicted by theory. The effect of consolidation of consumption efficiency is difficult to interpret from these findings. One significant finding is that, after consolidation, dollars pledged per donor, which is the size of the average donation, decreases by $13.52. The negative coefficient seems to indicate a decrease in consumption efficiency. However, although insignificant, the positive coefficients on the giving per employee (5.570) and participation (0.0183) variables indicate that consumption efficiency could actually have increased following the consolidation. The negative and significant coefficient on average gift amount (-

13.52) might also support this contradictory conclusion, because average gift size in affected by selection—increases in participation are nearly always among smaller donors, and drive down average gift size. I find no statistically significant effect of consolidation on cost per employee or cost per dollar raised, although the positive coefficient on cost per employee indicates that consolidation increases costs and decreases production efficiency. One possibility is that one-time costs from consolidation expenses are driving this result, leading to the addition of a new model that separates initial effects of consolidation from longer-term effects. This new model will be shown in Table 43.

Table 42 differs from Table 41 by including group-specific time trends to account for any pre-treatment differences in the trajectories of the two groups. The coefficients on the treatment group time trend (row 3 in the table) are insignificant, indicating that this is not an important control. Unsurprisingly, then, the results in Table 42 have the same signs as those in Table 41. I conclude that trends occurring prior to consolidation are not driving the surprising results.

Table 43 shows the preferred model for analyzing the effects of consolidation. This model relaxes the assumption that consolidation leads to an immediate and permanent shift in efficiency measures. After relaxing this assumption, the results change dramatically. Consolidation is associated with a significant decrease in dollars pledged per employee of $18.57, indicating a decrease in consumption efficiency. It is also associated with an increase in the time trend for the treated group (row 4 of the table, 3.019), which, although insignificant, indicates that the effect may be time-limited. The conclusion about decreasing consumption efficiency after mergers is weakly supported by a negative, non-significant decrease in participation and a positive, non-significant increase in dollars pledged per donor, or average gift, which probably indicates a decrease in smaller gifts after consolidation. These negative outcomes, may also be mitigated over time, although the coefficients are non-significant. These results have the expected signs, but are not statistically distinguishable from zero.

The inclusion of a differential post-treatment time trend also changes the relationship between consolidation and production efficiency, measured by cost per employee. There is an initial decrease in costs, although it is non-significant. The time trend increases, indicating a non-significant, short-run effect. The overall effect of consolidation on performance, measured by cost per dollar raised, is positive, but non-significant. If significant, the positive coefficient on cost per dollar raised would indicate that production efficiency may outweigh consumption efficiency in determining overall performance. However, in the absence of a statically significant result, one cannot determine which effect is stronger.

The results of Table 43 can also be used to understand the effect of scale on CFC outcomes, after controlling for consolidation, fixed effects, and other zone-level variables. The coefficients on the employee variables in Columns 4 show that program costs decrease as the number of employees covered by a zone increases, with the effect diminishing as the size increases. In contrast, column 5 shows that there is no effect of number of employees on cost per dollar raised. The number of employees seems to lower costs but also lower giving, on average. These results indicate that there are no overall economies of scale in the CFC.

Table 41. OLS Regression Results

	(1) Per Employee Gift Amount		(2) Proportion Employees Giving		(3) Average Gift Amount		(4) Budgeted Cost Per Employee		(5) Budgeted Cost Per Dollar Given	
Treated × Post-Consolidation	5.570	(4.212)	0.0183	(0.0163)	-13.52*	(6.227)	0.593	(1.050)	-0.0137	(0.00920)
Employees (1000s)	-2.455***	(0.657)	-0.00931***	(0.00245)	-0.245	(0.797)	-0.448**	(0.163)	-0.000751	(0.00204)
Employees × Employees (1000s)	0.00918**	(0.00312)	0.0000310**	(0.0000114)	0.00583	(0.00307)	0.00161*	(0.000777)	-0.000000905	(0.00000702)
Per Cap Personal Income ($1000s)	-1.190*	(0.521)	0.000213	(0.00229)	-1.111	(1.713)	0.149	(0.265)	0.00433	(0.00506)
Unemployment Rate	-65.93	(90.50)	-0.251	(0.441)	109.5	(297.8)	57.73	(69.49)	1.689	(1.554)
Average Length of Service	-2.400	(4.431)	-0.00723	(0.0140)	-18.52	(11.97)	-2.658	(1.677)	-0.0396	(0.0417)
Average Age	-3.982	(6.301)	-0.0324	(0.0313)	20.11	(19.59)	3.080	(3.543)	0.0808	(0.0727)
Average Salary ($)	0.00203	(0.00103)	0.00000812*	(0.00000357)	-0.00237	(0.00126)	0.000353	(0.000246)	0.000000252	(0.00000152)
Proportion Female	-244.3	(274.8)	-0.501	(0.915)	-468.9	(605.8)	-43.53	(79.18)	0.608	(0.920)
Proportion Permanent Status	-18.75	(98.83)	-0.332	(0.377)	223.6	(311.6)	-23.52	(41.89)	-0.788	(0.721)
Proportion Professional Category	-84.45	(179.8)	-0.223	(0.742)	-409.6	(723.9)	-46.42	(83.97)	-0.803	(1.395)
Proportion Administrative Category	-126.6	(145.4)	-0.729	(0.502)	621.9	(369.8)	-50.63	(50.57)	-0.952	(1.050)
Proportion Uniformed Military	-23.64	(18.43)	-0.0960	(0.0669)	-93.94*	(39.75)	-4.147	(2.924)	-0.00837	(0.0443)
Proportion Postal Service	-25.77	(19.18)	-0.0801	(0.0830)	-131.3*	(64.13)	1.037	(7.575)	0.179	(0.218)
Offers Online Giving	-1.499	(2.799)	-0.0138	(0.0106)	9.960	(6.735)	0.0190	(0.844)	0.00457	(0.0128)
Zone and Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Observations	250		250		250		250		250	
Adjusted R^2	0.809		0.781		0.920		0.501		0.564	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors, clustered at the (consolidated) zone level. Sample is consolidated records from CFC. Campaigns are included in the analysis sample if and only if they have an observable simple consolidation. The post-consolidation indicator is triggered by the first consolidation in 2009 or later.

Table 42. OLS Regression Results with Treatment-Specific Time Trends

	(1) Per Employee Gift Amount		(2) Proportion Employees Giving		(3) Average Gift Amount		(4) Budgeted Cost Per Employee		(5) Budgeted Cost Per Dollar Given	
Treated × Post-Consolidation	3.969	(4.723)	0.0129	(0.0175)	-6.713	(6.640)	0.241	(1.115)	-0.0149	(0.0123)
Time	-1.964	(1.976)	-0.0115	(0.00687)	17.42**	(5.617)	-1.105	(0.847)	-0.0149	(0.0222)
Treated × Time	1.226	(1.127)	0.00406	(0.00360)	-5.212	(2.804)	0.269	(0.333)	0.000913	(0.00553)
Employees (1000s)	-2.419***	(0.661)	-0.00919***	(0.00248)	-0.398	(0.837)	-0.440**	(0.161)	-0.000724	(0.00194)
Employees × Employees (1000s)	0.00890**	(0.00319)	0.0000301*	(0.0000115)	0.00701*	(0.00312)	0.00155*	(0.000766)	-0.00000111	(0.00000627)
Per Cap Personal Income ($1000s)	-1.127*	(0.546)	0.000423	(0.00219)	-1.381	(1.579)	0.163	(0.273)	0.00438	(0.00525)
Unemployment Rate	-60.99	(91.30)	-0.235	(0.443)	88.53	(285.0)	58.81	(69.68)	1.692	(1.570)
Average Length of Service	-3.138	(4.684)	-0.00967	(0.0140)	-15.38	(10.56)	-2.820	(1.849)	-0.0401	(0.0445)
Average Age	-4.271	(5.960)	-0.0333	(0.0299)	21.34	(16.86)	3.017	(3.422)	0.0806	(0.0717)
Average Salary ($)	0.00223*	(0.000977)	0.00000879*	(0.00000352)	-0.00322*	(0.00129)	0.000397	(0.000241)	0.000000401	(0.00000192)
Proportion Female	-270.7	(261.7)	-0.589	(0.859)	-356.6	(552.9)	-49.33	(74.36)	0.588	(0.867)
Proportion Permanent Status	-33.26	(106.0)	-0.380	(0.397)	285.2	(304.2)	-26.70	(44.67)	-0.799	(0.766)
Proportion Professional Category	-94.88	(178.0)	-0.257	(0.729)	-365.2	(681.5)	-48.71	(84.36)	-0.811	(1.425)
Proportion Administrative Category	-141.2	(144.2)	-0.777	(0.483)	684.0	(366.1)	-53.84	(52.81)	-0.963	(1.098)
Proportion Uniformed Military	-25.85	(19.10)	-0.103	(0.0717)	-84.58	(42.86)	-4.631	(3.201)	-0.0100	(0.0480)
Proportion Postal Service	-29.13	(20.62)	-0.0912	(0.0880)	-117.1	(65.58)	0.299	(7.143)	0.176	(0.207)
Offers Online Giving	-1.875	(2.948)	-0.0151	(0.0109)	11.56	(6.647)	-0.0636	(0.927)	0.00429	(0.0140)
Zone and Year FE	Yes		Yes		Yes		Yes		Yes	
Observations	250		250		250		250		250	
Adjusted R^2	0.809		0.781		0.923		0.501		0.562	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors, clustered at the (consolidated) zone level. Sample is consolidated records from CFC. Campaigns are included in the analysis sample if and only if they have an observable simple consolidation. The post-consolidation indicator is triggered by the first consolidation in 2009 or later.

Table 43. OLS Regression Results with Treatment-Specific Time Trends Affected by Treatment

	(1) Per Employee Gift Amount		(2) Proportion Employees Giving		(3) Average Gift Amount		(4) Budgeted Cost Per Employee		(5) Budgeted Cost Per Dollar Given	
Treated × Post-Consolidation	-18.57*	(8.733)	-0.0582	(0.0423)	19.98	(32.53)	-1.690	(2.301)	0.0105	(0.0589)
Time	-2.244	(1.918)	-0.0124	(0.00690)	17.76**	(5.625)	-1.129	(0.855)	-0.0146	(0.0227)
Treated × Time	-0.296	(1.541)	-0.000744	(0.00446)	-3.409	(3.473)	0.139	(0.279)	0.00262	(0.00435)
Treated × Post-Consolidation × Time	3.019	(1.526)	0.00953	(0.00586)	-3.576	(4.243)	0.259	(0.282)	-0.00340	(0.00675)
Per Cap Personal Income ($1000s)	-1.173*	(0.558)	0.000279	(0.00214)	-1.327	(1.585)	0.159	(0.272)	0.00443	(0.00520)
Unemployment Rate	-44.97	(86.24)	-0.184	(0.429)	69.55	(282.5)	60.19	(70.95)	1.674	(1.597)
Employees (1000s)	-2.334***	(0.625)	-0.00893***	(0.00238)	-0.498	(0.822)	-0.433**	(0.157)	-0.000819	(0.00189)
Employees × Employees (1000s)	0.00865**	(0.00309)	0.0000293*	(0.0000113)	0.00730*	(0.00308)	0.00153*	(0.000758)	-0.000000837	(0.00000613)
Average Length of Service	-2.884	(4.615)	-0.00887	(0.0136)	-15.68	(10.45)	-2.798	(1.831)	-0.0404	(0.0443)
Average Age	-5.381	(6.236)	-0.0368	(0.0304)	22.65	(16.64)	2.922	(3.416)	0.0818	(0.0699)
Average Salary ($)	0.00217*	(0.000952)	0.00000860*	(0.00000348)	-0.00315*	(0.00131)	0.000392	(0.000241)	0.000000469	(0.00000192)
Proportion Female	-276.6	(264.4)	-0.607	(0.886)	-349.7	(563.3)	-49.84	(74.93)	0.594	(0.855)
Proportion Permanent Status	-22.65	(116.3)	-0.347	(0.426)	272.7	(306.4)	-25.79	(44.84)	-0.811	(0.752)
Proportion Professional Category	-86.95	(184.5)	-0.232	(0.763)	-374.6	(688.9)	-48.03	(84.46)	-0.820	(1.415)
Proportion Administrative Category	-111.1	(137.3)	-0.682	(0.467)	648.3	(367.3)	-51.26	(51.63)	-0.997	(1.049)
Proportion Uniformed Military	-22.35	(17.39)	-0.0922	(0.0667)	-88.73*	(41.58)	-4.331	(3.055)	-0.0139	(0.0461)
Proportion Postal Service	-24.27	(18.89)	-0.0759	(0.0828)	-122.8	(65.76)	0.716	(7.260)	0.171	(0.217)
Offers Online Giving	-2.986	(2.630)	-0.0186	(0.0106)	12.87	(6.535)	-0.159	(0.960)	0.00554	(0.0160)
Zone and Year Fixed Effects	Yes		Yes		Yes		Yes		Yes	
Observations	250		250		250		250		250	
Adjusted R^2	0.812		0.783		0.923		0.499		0.560	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors, clustered at the (consolidated) zone level. Sample is consolidated records from CFC. Campaigns are included in the analysis sample if and only if they have an observable simple consolidation. The post-consolidation indicator is triggered by the first consolidation in 2009 or later.

3.8 Discussion

These results have implications for theory and policy regarding consolidation in the nonprofit sector. I use the CFC as a means to explore the extent to which sector structure vis-à-vis consolidation noticeably accomplishes professed goals of improving economies of scale and stimulating philanthropic behavior.

The findings in this paper are sensitive to the underlying assumptions of the model. The model with the least restrictive assumptions is my preferred model. Using this model, I conclude that consolidation decreases the consumption efficiency in the CFC, although the effect may be mitigated by time (or may not, as the coefficient on the time trend is insignificant). These results may indicate that the staff of the surviving zone are able to learn about the newly absorbed zone's employees and improve their relationships and customization of CFC operations to that zone over time.

The preferred model also suggests that consolidation may increase production efficiency, but that the effect is small (and here, insignificant). It seems that economies of scale are limited in the context of consolidation, perhaps because staff gradually increases their budget so that they can perform useful but time-intensive activities, such as coordinating activities over a larger area, working with a wider variety of volunteers, and customizing activities to a variety of audiences.

Finally, the preferred model suggests that the overall performance of the CFC does not change significantly following consolidation. In fact, the cost per dollar raised may increase initially, although this result is statistically insignificant, and the negative effect on the time trend indicates that this increase may be short lived. The benefits of consolidation are, at best, more modest than CFC administrators had hoped.

This work finds no evidence that economies of scale exist in workplace giving campaigns like the CFC. This result may give the CFC pause as it moves forward with consolidating the number of service areas from 100 to 37. Other types of workplace giving campaigns, like those conducted by United Way, operate at a much smaller scale. (There are over 1,200 United Way zones in the United States). Future research is needed to determine if these types of organizations, or indeed other non-workplace giving nonprofits, are operating at a part of the cost curve where economies of scale might apply.

The present paper is the first to look at the effect of changing the size of territory covered by a service provider through a governmental contract. The results indicate that consolidating small contracts into larger ones is not an effective way to decrease costs or increase efficiency, at least in this context. Unfortunately, I cannot observe fine-grained details about the contracting relationship, such as the identity of the nonprofit intermediary, the qualifications of the staff, or the specific activities conducted. The mechanisms underlying the decrease in consumption efficiency and insignificant change in production efficiency cannot be determined by this work, and should be the subject of future research.

Finally, the CFC is unusual because its clients are government employees. Contracts between the government and nonprofit providers typically provide services to members of the public. Future research should examine if changing the size of the service area leads to efficiency improvements in other contracting relationships.

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Biography

Danielle Lee Vance-McMullen (née Vance) was born on July 13, 1983, in Mason City, Iowa. She was raised in Floyd, Iowa, and graduated from Charles City High School in 2001. In 2005, Danielle earned a B.S. in Marketing from Iowa State University. She also earned a Master's of Public Affairs in Nonprofit Management and a Master's of Arts degree in Philanthropic Studies from Indiana University Purdue University, Indianapolis in 2010. Danielle received her Ph.D. in Public Policy from the Sanford School of Public Policy at Duke University in 2017. She earned a M.A. in Economics from Duke University en route in 2014.

Danielle's dissertation research at Duke was funded by the Horowitz Foundation for Social Policy and the Center for the Study of Philanthropy and Voluntarism at Duke University. Danielle also received several honors and awards that supported her graduate studies, including the James B. Duke fellowship, the Aelene Webb Dissertation Research Award, several Graduate School Summer Research Fellowships, and numerous Conference Travel Grants from the Sanford School of Public Policy. During her time at Duke, Danielle also received funding from the Kenan Institute for Ethics and the Association of Researchers on Nonprofit Organizations and Voluntary Associations.

In the fall of 2017, Danielle will be joining the faculty of the University of Memphis as an Assistant Professor in the Department of Public and Nonprofit Administration.